

AD-A181 609

COMPARISON OF MODEL-BASED SEGMENTATION ALGORITHMS FOR
COLOR IMAGES (U) NAVAL POSTGRADUATE SCHOOL MONTEREY CA
T RUPELT MAR 87

1/1

UNCLASSIFIED

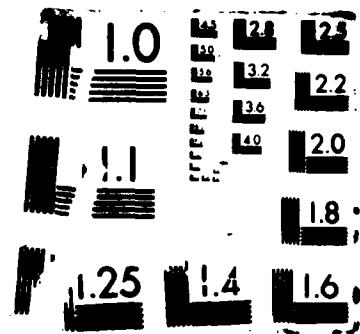
F/G 12/9

ML

END

1/1

1/1



AD-A181 609

NAVAL POSTGRADUATE SCHOOL
Monterey, California



DTIC
ELECTE
JUN 26 1987
S D E

THESIS

COMPARISON OF MODEL-BASED
SEGMENTATION ALGORITHMS FOR COLOR IMAGES

by

Timur Kupeli

March 1987

Thesis Advisor: Charles W. Therrien

Approved for public release; distribution is unlimited

Original contains color
plates: All DTIC reproductions
will be in black and
white.

87 6 23 067

AD A181 609

REPORT DOCUMENTATION PAGE

1a REPORT SECURITY CLASSIFICATION UNCLASSIFIED			1b. RESTRICTIVE MARKINGS	
2a SECURITY CLASSIFICATION AUTHORITY			3 DISTRIBUTION/AVAILABILITY OF REPORT Approved for public release; distribution is unlimited	
2b DECLASSIFICATION/DOWNGRADING SCHEDULE			5 MONITORING ORGANIZATION REPORT NUMBER(S)	
4 PERFORMING ORGANIZATION REPORT NUMBER(S)			5 MONITORING ORGANIZATION REPORT NUMBER(S)	
6a NAME OF PERFORMING ORGANIZATION Naval Postgraduate School		6b OFFICE SYMBOL (If applicable) 62	7a NAME OF MONITORING ORGANIZATION Naval Postgraduate School	
6c ADDRESS (City, State, and ZIP Code) Monterey, California 93943-5000			7b ADDRESS (City, State, and ZIP Code) Monterey, California 93943-5000	
8a NAME OF FUNDING/SPONSORING ORGANIZATION		8b OFFICE SYMBOL (If applicable)	9 PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER	
8c ADDRESS (City, State, and ZIP Code)			10 SOURCE OF FUNDING NUMBERS	
			PROGRAM ELEMENT NO	PROJECT NO
			TASK NO	WORK UNIT ACCESSION NO
11 TITLE (Include Security Classification) COMPARISON OF MODEL-BASED SEGMENTATION ALGORITHMS FOR COLOR IMAGES				
12 PERSONAL AUTHOR(S) Kupeli, Timur				
13a TYPE OF REPORT Master's Thesis		13b TIME COVERED FROM TO	14 DATE OF REPORT (Year, Month, Day) 1987 March	15 PAGE COUNT 71
16 SUPPLEMENTARY NOTATION				
17 COSATI CODES			18 SUBJECT TERMS (Continue on reverse if necessary and identify by block number)	
FIELD	GROUP	SUB-GROUP	Maximum Likelihood, Maximum A Posteriori, Markov Random Field, Karhunen-Loeve Transformation	
19 ABSTRACT (Continue on reverse if necessary and identify by block number) The objective of this thesis is to develop segmentation methods for multi-channel and single channel images, and compare these methods. The segmentation algorithms are based on a linear model for the image textures and on inverse filtering to estimate the image textures and their regions. Two specific methods are compared 1) A multichannel filtering algorithm that simultaneously models the three separate signals representing the intensity of red, green, and blue as a function of spatial position and 2) A single channel model applied to a combined image resulting from performing a Karhunen-Loeve transformation on the three signal components. Results of the multichannel image segmentation and the Karhunen-Loeve transformed one-channel image segmentation are presented and compared.				
20 DISTRIBUTION/AVAILABILITY OF ABSTRACT <input checked="" type="checkbox"/> UNCLASSIFIED/UNLIMITED <input type="checkbox"/> SAME AS RPT <input type="checkbox"/> DTIC USERS			21 ABSTRACT SECURITY CLASSIFICATION UNCLASSIFIED	
22a NAME OF RESPONSIBLE INDIVIDUAL Prof. C.W. Therrien			22b TELEPHONE (Include Area Code) 408-646-3347	22c OFFICE SYMBOL 62Ti

Approved for public release; distribution is unlimited.

Comparison of Model-Based
Segmentation Algorithms For Color Images

by

Timur Kupeli
Lieutenant JG, Turkish Navy
B.S., Turkish Naval Academy, 1980.

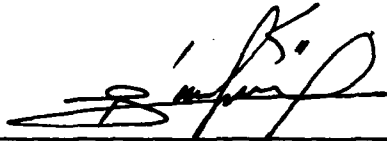
Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN ELECTRICAL ENGINEERING

from the

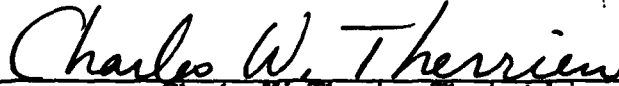
NAVAL POSTGRADUATE SCHOOL
March 1987

Author:

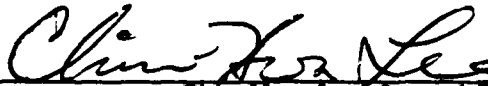


Timur Kupeli

Approved by:



Charles W. Therrien, Thesis Advisor



Chin-Hwa Lee, Second Reader



Harriett Rigas, Chairman, Department of
Electrical and Computer Engineering



Gordon E. Schacher,
Dean of Science and Engineering

ABSTRACT

The objective of this thesis is to develop segmentation methods for multichannel and single channel images, and compare these methods. The segmentation algorithms are based on a linear model for the image textures and on inverse filtering to estimate the image textures and their regions. Two specific methods are compared 1) A multichannel filtering algorithm that simultaneously models the three separate signals representing the intensity of red, green, and blue as a function of spatial position and 2) A single channel model applied to a combined image resulting from performing a Karhunen-Loève transformation on the three signal components. Results of the multichannel image segmentation and the Karhunen-Loève transformed one-channel image segmentation are presented and compared.

Keywords: maximum likelihood; Markov random fields; computer programs; trees

Accession For	
NTIS GRA&I	<input checked="" type="checkbox"/>
DTIC TAB	<input type="checkbox"/>
Unannounced	<input type="checkbox"/>
Justification	
By	
Distribution/	
Availability Codes	
Dist	Avail and/or Special
A-1	



TABLE OF CONTENTS

I.	INTRODUCTION	7
II.	IMAGE SEGMENTATION USING A MULTICHANNEL FILTERING MODEL	9
	A. MODEL DEVELOPMENT	9
	B. ALGORITHM DEVELOPMENT	12
	1. Filter Parameter Estimation Method	13
	2. Multichannel Segmentation Method	18
III.	KARHUNEN-LOÈVE TRANSFORMATION AND ONE- CHANNEL IMAGE SEGMENTATION	25
	A. MODEL DEVELOPMENT	25
	B. ALGORITHM DEVELOPMENT	27
	1. Correlation Function Estimation	27
	2. Karhunen-Loève Transformation Matrix	28
	3. Karhunen-Loève Transformation	28
	C. ONE-CHANNEL IMAGE SEGMENTATION	28
IV.	RESULTS AND COMPARISON OF THE METHODS	30
V.	CONCLUSIONS	40
	APPENDIX A: RELAXATION METHOD	41
	APPENDIX B: FILTER PARAMETER ESTIMATION AND MULTICHANNEL SEGMENTATION	44
	APPENDIX C: KARHUNEN-LOÈVE TRANSFORMATION	46
	APPENDIX D: COMPUTER PROGRAMS FOR MULTICHANNEL IMAGE SEGMENTATION	47
	APPENDIX E: PROGRAMS FOR K-L TRANSFORMATION, AND ONE-CHANNEL SEGMENTATION	57
	LIST OF REFERENCES	69
	INITIAL DISTRIBUTION LIST	70

LIST OF TABLES

1. ENERGY DISTRIBUTION BETWEEN TRANSFORMED IMAGE
CHANNELS 27

LIST OF FIGURES

2.1	2-D Multichannel Image Model	11
2.2	Typical estimation windows for two textures	14
2.3	Selection of the Size of the Windows for Mean Vector Estimation	15
2.4	State support region of the point s for MAP estimation	21
2.5	A Set of States 1 's, 0 's adjacent to S for MAP Region Estimate	23
4.1	Two-Texture Color Image	32
4.2	ML Region Estimation of Figure 4.1 Image	33
4.3	MAP Region Estimation of Figure 4.1 Image	33
4.4	Color Image Containing Two-Texture	34
4.5	ML Region Estimation of Figure 4.4 Image	35
4.6	MAP Region Estimation of Figure 4.4 Image	35
4.7	First Channel of K-L Transformation of Figure 4.1 Image	36
4.8	ML Region Estimation of Figure 4.7	37
4.9	MAP Region Estimation of Figure 4.7	37
4.10	K-L Transformed Single Channel Image of Figure 4.4	38
4.11	ML Segmentation of Figure 4.10	39
4.12	MAP Segmentation of Figure 4.10	39
A.1	Relaxation Method Segmentation with $c = 0.1$	42
A.2	Relaxation Method Result with $c = 0.9$	43

I. INTRODUCTION

Segmentation techniques are among the most important considerations in the development of the automated image processing systems. Two related algorithms using 2-D *linear prediction models* and the *Karhunen-Loève transformation* for multichannel and color image segmentation are developed and compared in this thesis.

The purpose of segmentation is to partition an image into a set of simpler homogeneous regions. The regions may consist of different gray level, different textures, colors, etc. In some cases an "image" may consist of several spectral components. For example, a color image consists of three separate signals representing the intensity of red, green, and blue as a function of spatial position. If we represent each of these signals by functions $F_r(n,m)$, $F_b(n,m)$, and $F_g(n,m)$, the image is represented by a vector quantity

$$\mathbf{F}(n,m) = \begin{bmatrix} F_r(n,m) \\ F_b(n,m) \\ F_g(n,m) \end{bmatrix} \quad (1.1)$$

where n and m represent spatial coordinates. We call such an image, consisting of more than one two dimensional (2-D) signal, a *multichannel image*.

In this thesis, a method based upon *linear prediction* is evaluated experimentally. This method has been developed [Ref. 1] for monochrome images and extended to color images [Ref. 2]. That method uses *maximum likelihood (ML)* and *maximum a posteriori (MAP)* estimation to segment multichannel images into regions of similar textures. The linear prediction is a filtering of the multichannel image to estimate the gray level at a particular spatial coordinate from the gray levels at neighboring positions. It is implemented as a 2-D linear filtering operation. The algorithm uses a previously-determined set of parameters corresponding to the mean of the data in each channel, the covariance matrix of the prediction error, and the weighting coefficients of the estimation filter for each specific texture type.

The method discussed above is compared to a variant of this method based on the *Karhunen-Loève (K-L) transformation*. The K-L transformation allows the several

components of an image to be combined into a single image that retains most of the energy in the original image. Hunt and Kubler [Ref. 3] found that for image restoration, Karhunen-Loève transformation followed by single channel image processing worked nearly as well as multichannel image processing. It was desired to see if the Karhunen-Loève transformation would be equally effective for segmentation. In this part of the work, the K-L transformation has been developed to reduce the 3-channel color problem to a 1-channel problem and the segmentation was performed for the one-channel image. Karhunen-Loève transformation is based upon the statistical characteristics of an image. The advantage of this approach is computational savings; only about one ninth the number of computations is required for this method.

The remainder of this thesis is organized as follows. Chapter II discusses the model and the algorithms used to perform the multichannel image segmentation employing techniques of linear prediction [Ref. 4]. A general class of linear filtering models for texture is first presented. An algorithm is then developed to estimate the filter parameters from a multichannel image. Then, the multichannel image segmentation algorithm is described.

Chapter III presents the models and the algorithms to perform the Karhunen-Loève transformation and one-channel image segmentation. First, the algorithms for determining the eigenvectors and the eigenvalues of the correlation matrix are developed. Then, the transformation using a 3-channel image is presented. Finally, the one-channel image segmentation algorithm is discussed. The examples demonstrating the application of the segmentation methods for color images are presented and compared in Chapter IV. Chapter V has the conclusions about the multichannel image segmentation and one-channel image segmentation.

In Appendix A, the *Relaxation Method* is described briefly as an alternative to the *maximum a posteriori* region estimation for monochrome images. Results are compared with the MAP method. In each of Appendices B and C, the description and use of the computer programs for the multichannel image segmentation and the one-channel image segmentation are presented. The computer program for multichannel image segmentation is contained in Appendix D. The Karhunen-Loève transformation and one-channel image segmentation computer programs are contained in Appendix E. These programs are written in FORTRAN, compiled using Version 4.2 under the VAX / VMS Version 4.1 operation system.

II. IMAGE SEGMENTATION USING A MULTICHANNEL FILTERING MODEL

In this chapter, a multichannel image segmentation algorithm based upon a 2-D linear filtering model is presented. The multichannel images used in this work are color images with three channels representing the red, green, and blue components. The linear filtering model is used to develop approximate expressions for the multivariate probability density functions in terms of the filter error residuals for the entire set of points representing an image. The density expressions are used in the formulation and solution of the multichannel image segmentation problem. It is assumed that the multichannel images contain multiple regions of homogeneous texture. This is found to be the case in dealing with aerial photographs of natural terrain.

The problem of multichannel image segmentation is addressed as an estimation problem for two regions of texture. *Maximum likelihood (ML)* and *maximum a posteriori (MAP)* region estimates using a *Markov random field* to model region transitions are developed.

This chapter consists of two sections. The first section describes the linear filtering model and develops an expression for the image probability density function in terms of filter error residuals. The last section deals with the algorithm that is developed for the texture estimation and the multichannel image segmentation. The results of texture estimation and image segmentation are presented in Chapter IV.

A. MODEL DEVELOPMENT

In this section, a 2-D multichannel *autoregressive-moving average (ARMA)* model [Ref. 5] is first discussed. Then, we concentrate on the multichannel *autoregressive (AR)* model with *Gaussian white noise* inputs [Ref. 6]. The development parallels that in [Ref. 1]. A multichannel image is represented by a vector signal $\underline{x}^h(n,m)$ where (n,m) are spatial coordinates and the superscript h is an index representing the texture type. A 2-D multichannel image is shown in Figure 2.1. A texture of type h is then modeled in general by a multichannel ARMA process defined by

$$F^h(n,m) = - \sum_{i=0}^{P-1} \sum_{j=0}^{Q-1} A_{ij}^h F^h(n-i,m-j) + \sum_{\beta} B_{ij}^h W^h(n,m) \quad (2.1)$$

$(i,j) \neq (0,0)$

$$F_m^h(n,m) = F^h(n,m) + Q^h \quad (2.2)$$

for $h = 0,1, n = 1,\dots,N, m = 1,\dots,M$, where A_{ij}^h and B_{ij}^h are set of filter weighting coefficient matrices of size K by K . $W^h(n,m)$ are a set of independent identically distributed zero-mean random variables, Q is a constant representing the mean value of the image, and β is finite-extent mask covering the filtered points. $F^h(n,m)$, $W^h(n,m)$, and Q^h are vectors of size K , the number of channels in the image. The matrices A_{ij}^h are the key parameters in the linear model. For a first quadrant filter with a $P \times Q$ region of support, there are PQ A_{ij}^h matrices with $A_{00}^h = I$, an identity matrix.

For the *auto-regressive (AR)* or *all-pole* model we have $B_{ij}^h = \delta_{ij}^I$ and so that Equation 2.1 reduces to

$$F^h(n,m) = - \sum_{i=0}^{P-1} \sum_{j=0}^{Q-1} A_{ij}^h F^h(n-i,m-j) + W(n,m) \quad (2.3)$$

$(i,j) \neq (0,0)$

If the vectors f , w , and g represent an ordered set of the corresponding image points, then Equation 2.2 and Equation 2.3 are written in a matrix formulation as

$$A(f - g) = W - A_0 f_0 \quad (2.4)$$

where A and A_0 are matrices whose nonzero elements are derived from the terms A_{ij} in Equation 2.1 and f_0 represents a set of boundary conditions with support outside of the regions. Since the terms $W(n,m)$ are independent with probability density function (PDF) p_w , One can solve Equation 2.4 for W and express the multivariate probability density function for the image conditioned on the boundary values as

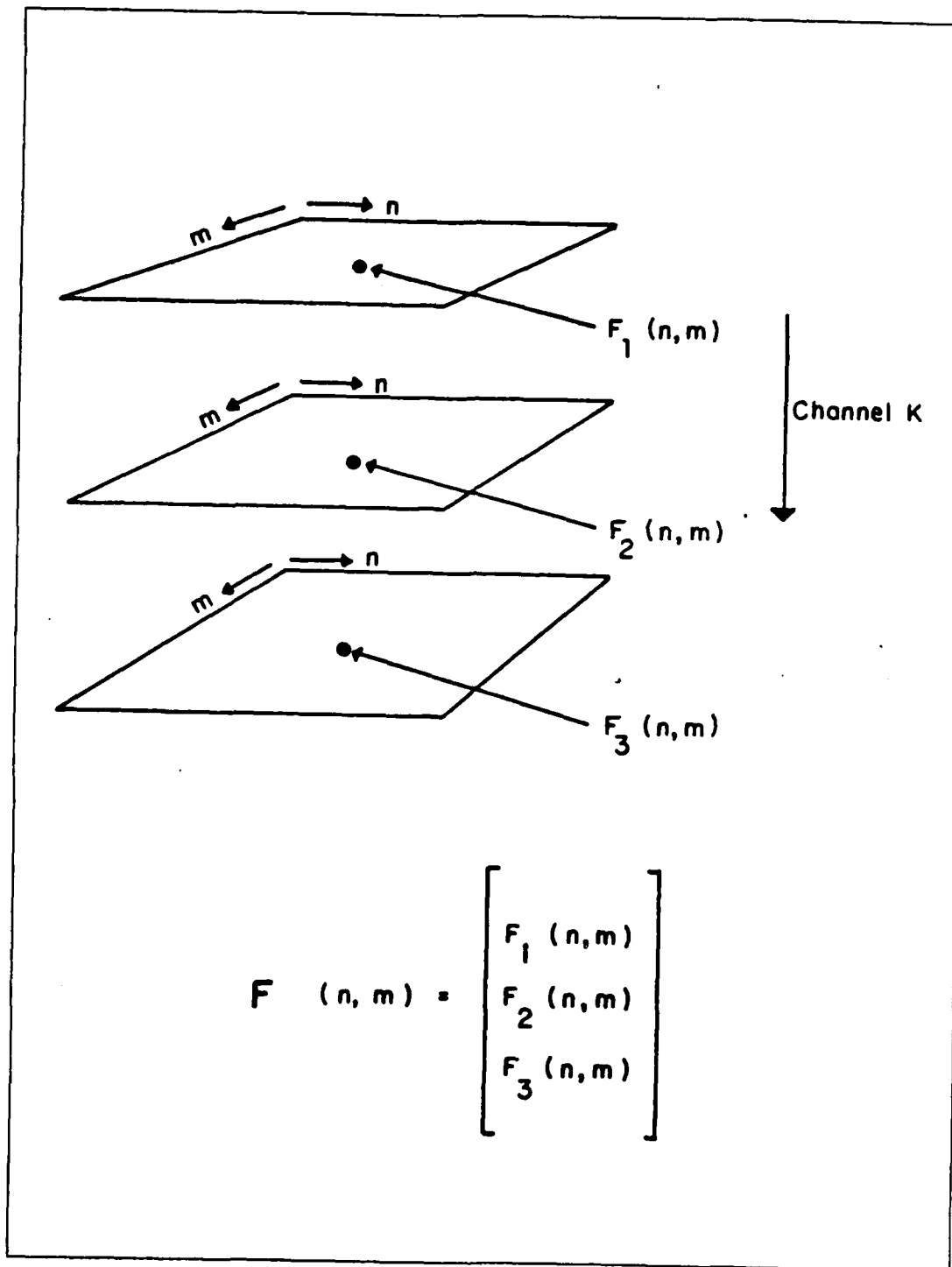


Figure 2.1 2-D Multichannel Image Model.

$$P_{f|f_0}(f|f_0) = \frac{1}{|A^{-1}|} p_w(A(f-g) + A_0 f_0) \quad (2.5)$$

$$= \prod_{(n,m) \in R} p_w(E(n,m))$$

where the notation $E(n,m)$ is used to represent the ordered components of the vector $A(f-g) + A_0 f_0$. If the boundary conditions, f_0 , are temporarily ignored, then

$$E(n,m) = A(f - g) \quad (2.6)$$

and the terms $E(n,m)$ in Equation 2.5 are computed from

$$E^h(n,m) = \sum_{i=0}^{P-1} \sum_{j=0}^{Q-1} A_{ij}^h E^h(n-i, m-j) \quad (2.7)$$

$(i,j) \neq (0,0)$

The filter of Equation 2.7 which computes $E^h(n,m)$ from $E^h(n,m)$ is referred to as the '*prediction error filter*'. One can think of Equation 2.7 as producing an estimate or *prediction* $\hat{E}(n,m)$ of the image at point (n,m) and then forming an error $E(n,m)$ as a difference $E(n,m) - \hat{E}(n,m)$. This process is known as 2-D linear prediction and is fundamental to performing multichannel image segmentation.

B. ALGORITHM DEVELOPMENT

In the multichannel segmentation problem, it is assumed that the image consists of multiple connected regions of known texture types, but that the region boundaries and the number of regions are not known. The segmentation of the image is treated as a supervised learning problem, since the regions are considered to consist of known texture types. In this section, the multichannel image segmentation algorithm for textured images is discussed.

An overview of the method is as follows. Given a multichannel image of each texture, filter parameters are estimated by computing the covariance matrix from a set of data and solving the Normal equations corresponding to the model of Equation 2.3 . In this case the '*correlation method*' of linear prediction is used to compute the covariance matrix. The filter parameters are derived from a statistical analysis of the textured images, because the image model discussed in the previous section is based upon statistical properties.

Once the filter parameters are known the filters are used to perform the segmentation. The filter weighting coefficients are used to calculate the prediction errors $E^h(n,m)$ of two textures (n,m) . Then, a maximum likelihood (ML) region estimate is developed using the prediction errors and the covariance matrices for image. The ML estimate is used as a basis to determine an approximate *maximum a posteriori* (MAP) region estimate. The MAP region estimation utilizes an underlying Markov structure for the region statistics to produce an accurate segmentation.

1. Filter Parameter Estimation Method

The prediction error filter is a *finite-extent impulse response (FIR)* or *nonrecursive* filter with selectable mask size and quarterplane region of support. It is always stable. The inverse of the filter used in Equation 2.3 is an all-pole filter (the AR filter). The filter parameter estimation problem requires calculating \bar{E}^h , Σ_w^h , and A^h by statistical analysis of data in an estimation window containing the desired texture, where the quantity \bar{E}^h is a mean vector of the average gray level of the image in each of the channels, and Σ_w^h is a covariance matrix of the multichannel white noise

$$\Sigma_w^h = E [\bar{E}^h(n,m) (\bar{E}^h(n,m))^T] \quad (2.8)$$

the term Σ_w^h is also referred to as the prediction error covariance matrix, since in a linear prediction problem it represents the covariance of the quantities $\bar{E}(n,m)$ defined in Equation 2.7 . Since Σ_w^h is not in general a diagonal matrix, we see that the 'white noise' is uncorrelated within each channel but correlated between channels.

The covariance of the multichannel white noise (the prediction error covariance) and the filter coefficients will be obtained by estimating the correlation function of the image and solving a set of Normal equations as discussed below. The

correlation function itself is estimated from data in a window containing a sample of the desired texture. Two estimation windows are depicted in Figure 2.2 for two different textures in the multichannel image. The reader should realize that the estimation windows do not have to come from the image to be segmented; they can be selected from any image containing the same type of texture.

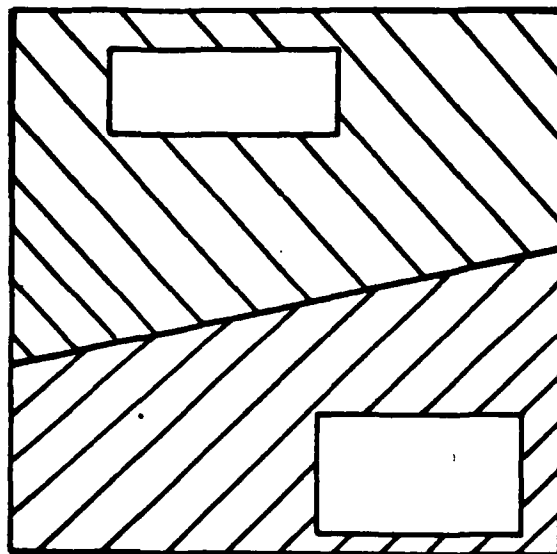


Figure 2.2 Typical estimation windows for two textures.

a. Mean Vector Estimation

In order to model the multichannel image by Equations 2.2 and 2.3 the mean vector of the multichannel image has to be estimated. Knowing \bar{M} and selecting the stationary estimation windows of two desired textures of \bar{E}_m , the zero mean 2-D multichannel image, \bar{E} , appearing in Equation 2.3 can be obtained by subtracting the mean vectors from the multichannel image. Thus, Equation 2.2 becomes

$$\bar{E}^h(n,m) = \bar{E}_m^h(n,m) - \bar{M}^h \quad (2.9)$$

where M^h corresponds to E^h in Equation 2.2, and the term M^h in Equation 2.9 are computed from

$$M^h = \begin{bmatrix} M_1^h \\ M_2^h \\ M_3^h \end{bmatrix} \quad (2.10)$$

where

$$M_k^h = \frac{1}{N' M'} \sum_{n=X_1}^{X_2} \sum_{m=Y_1}^{Y_2} E_k^h(n,m) \quad (2.11)$$

M_k^h is the mean estimate for the k^{th} channel of the h^{th} texture image. The limits X_1 , X_2 , Y_1 , Y_2 represents the edges of the window which is of size N' by M' . Therefore $N' = X_2 - X_1 + 1$, $M' = Y_2 - Y_1 + 1$, and $0 \leq X_1 < X_2 \leq N$, $0 \leq Y_1 < Y_2 \leq M$, and h represents the two textures of the multichannel image. All variables used in Equation 2.11 are depicted in Figure 2.3.

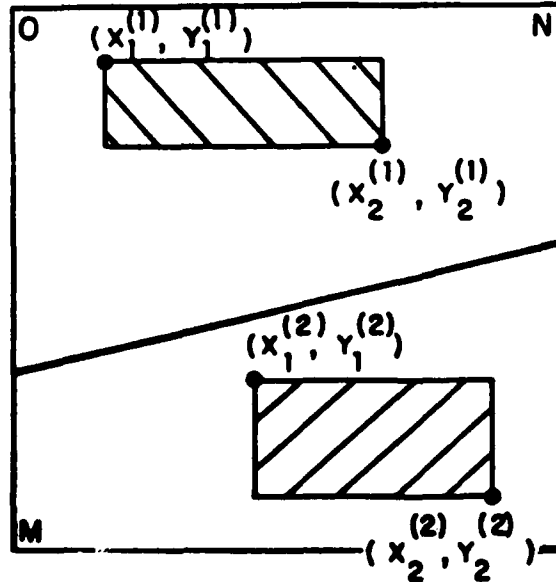


Figure 2.3 Selection of the Size of the Windows for Mean Vector Estimation.

b. Correlation Function Estimation

The correlation function of the zero mean, 2-D multichannel signal has to be calculated in order to estimate the multichannel white noise covariance or prediction error covariance, Σ_w^h , and the filter weighting coefficients, A_{ij}^h . The theoretical 2-D matrix correlation function for lag $\sim i, j \sim$ is given by

$$\begin{aligned} R^h(i, j) &= (R^h(-i, -j))^T \\ &= E[\mathbf{F}^h(n, m) \cdot (\mathbf{F}^h(n-i, m-j))^T] \end{aligned} \quad (2.12)$$

and can be estimated from the multichannel signal by

$$R^h(i, j) = \frac{1}{N' M'} \sum_{n=n_1}^{n_2} \sum_{m=m_1}^{m_2} \mathbf{F}^h(n, m) (\mathbf{F}^h(n-i, m-j))^T \quad (2.13)$$

where $R^h(i, j)$ is a matrix of size K by K , and n_1, n_2, m_1, m_2 are defined by

$$0 \leq n_1 = \max(X_1, X_1 + i) < n_2 = \min(X_2, X_2 + i) \leq N, \text{ and}$$

$$0 \leq m_1 = \max(Y_1, Y_1 + j) < m_2 = \min(Y_2, Y_2 + j) \leq M.$$

This matrix correlation function is used to form a larger block Toeplitz covariance matrix which is used to estimate the filter parameters. This is discussed next.

c. Filter Coefficients and Prediction Error Covariance

The prediction error filter weighting coefficients and the prediction error covariance must satisfy a set of linear equations known as the Normal Equations when the multichannel image is represented by the model in Equation 2.3.

Normal equations corresponding to Equation 2.3 can be written as

$$[R] \cdot [A] = [S] \quad (2.15)$$

where R is the correlation matrix for the signal, A is an appropriately ordered matrix of the filter coefficients, and S contains a single non-zero block Σ_w which is the prediction error covariance. The matrix R has three levels of partitioning and for any rectangular region of support is block Toeplitz with block Toeplitz blocks.

For a first quadrant filter with a $P \times Q$ region of support, The Normal equations that define Equation 2.15 have the specific form

$$\begin{bmatrix} R(0) & R(-1) & \dots & R(-P+1) \\ R(1) & R(0) & \dots & R(-P+2) \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ R(P-1) & R(P-2) & \dots & R(0) \end{bmatrix} \begin{bmatrix} A^0 \\ A^1 \\ \cdot \\ \cdot \\ A^{P-1} \end{bmatrix} = \begin{bmatrix} S^0 \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix} \quad (2.16)$$

where

$$R(i) = \begin{bmatrix} R(i,0) & R(i,-1) & \dots & R(i,-Q+1) \\ R(i,1) & R(i,0) & \dots & R(i,-Q+2) \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ R(i,Q-1) & R(i,Q-2) & \dots & R(i,0) \end{bmatrix} \quad (2.17)$$

$$= R^T(-i)$$

and where $R(i,j)$ is the matrix correlation function described in Equations 2.12 and 2.13
The quantities A^i and S^0 are defined by

$$A^i = \begin{bmatrix} A_{i,0} \\ A_{i,1} \\ \cdot \\ \cdot \\ A_{i,Q-1} \end{bmatrix} \quad (2.18)$$

and

$$S = \begin{bmatrix} \Sigma_w \\ 0 \\ \cdot \\ \cdot \\ 0 \end{bmatrix} \quad (2.20)$$

with $A_{00} = I$ and where A_{ij} and the partitions of S^0 are matrices of order K , the number of channels of image.

2. Multichannel Segmentation Method

An overview of the segmentation is as follows. By using a Gaussian probability density for the white noise in Equation 2.5, one can develop explicit estimates for the density functions in terms of the prediction errors $\underline{E}(n,m)$. From this one can form the conditions for ML and MAP estimation of the regions in the image. The theory leading to the estimates is explained below. A brief intuitive explanation of the process is given here.

As mentioned earlier the prediction error filters in Equation 2.3 can be considered as predicting the intensity of a pixel in each channel from data in the region adjacent to the vector of pixels. The prediction errors $\underline{E}^h(n,m)$ are the outputs of the filters. In the segmentation algorithm the prediction error is normalized in an expression involving the corresponding prediction error covariance. These normalized errors are compared in an appropriate formula to obtain the ML region estimate. When an area of texture is processed by a filter that is not matched to the texture, the normalized prediction error can be expected to be high. When the same area is processed by the filter that is matched to the texture, the prediction error can be expected to be low.

The 'maximum likelihood' region estimate, $ML(n,m)$, of texture class is achieved based on the prediction error covariance and the error estimates of the two desired textures for each pixel in the multichannel image. The $ML(n,m)$ region estimate assigns pixels to texture types without regard to the assignments of the adjacent pixels. Then, the 'maximum a posteriori' region estimate, $MAP(n,m)$, of texture class is achieved for a pixel and a desired number of adjacent pixels of two textures of the ML region estimation result. The MAP region estimation uses the Markov model that refers to the above description. The form of the Markov model and ML and MAP region estimates are presented in detail below.

a. Maximum Likelihood Region Estimation

It is supposed that a multichannel image has many regions, but that each region contains only one or another of two texture types. Given these regions, one can write the Equation 2.5 as

$$p(\underline{E} | R_i) = \prod_{(n,m)} p_{w_{hi}}(\underline{E}(n,m)) \quad i = 1, \dots, q \quad (2.21)$$

where the p_{wh} is the probability density function for the white noise source of type h_i within region R_i , and q is the number of regions. When the white noise term is Gaussian with density function (mean 0 and covariance Σ_w)

$$p_{\mathbf{W}}(\mathbf{W}) = \frac{1}{(2\pi)^{NM/2} |\Sigma_w|^{1/2}} \exp\left(-\frac{1}{2} \mathbf{W}^T \Sigma_w^{-1} \mathbf{W}\right) \quad (2.22)$$

then, taking minus twice the log of Equation 2.21 and applying Equation 2.22, we obtain for an N by M pixel multichannel image

$$\begin{aligned} & -2 \ln p(\mathbf{Z} | R_1, R_2, \dots, R_q) \\ &= \sum_{(n,m) \in R_1} ([\mathbf{Z}_h^1(n,m)]^T [\Sigma_h^1]^{-1} [\mathbf{Z}_h^1(n,m)] + \ln |\Sigma_h^1|) + \dots \\ &+ \sum_{(n,m) \in R_q} ([\mathbf{Z}_h^q(n,m)]^T [\Sigma_h^q]^{-1} [\mathbf{Z}_h^q(n,m)] + \ln |\Sigma_h^q|) \\ & \quad - NM \ln 2\pi \\ &= \sum_{i=1}^q \sum_{(n,m) \in R_i} ([\mathbf{Z}_h^i(n,m)]^T [\Sigma_h^i]^{-1} [\mathbf{Z}_h^i(n,m)] + \ln |\Sigma_h^i|) \\ & \quad - NM \ln 2\pi \end{aligned} \quad (2.23)$$

For maximum likelihood estimation, the number of regions q and the regions themselves are considered to be deterministic parameters of the density function. An ML estimate for these parameters is obtained by choosing values that maximize Equation 2.21 or, minimize Equation 2.23. Since $NM \ln 2\pi$ is constant value, the Equation 2.23 is minimized if every point (n,m) in the multichannel image to a region R_i of type h_i such that the term in brackets is minimum. Thus, one can write a ML region estimation for two textures as

$$ML_1(n,m) \underset{1}{\overset{0}{>}} ML_0(n,m) \quad (2.24)$$

where

$$ML_h(n,m) = [E^h(n,m)]^T [\Sigma_w^h]^{-1} [E^h(n,m)] + \ln |\Sigma_w^h| \quad (2.25)$$

for $h = 0, 1$, where the number above or below the inequality indicates the region class to which the pixel (n,m) is assigned. When the class is 1, the $ML(n,m)$ is assigned 1 for a white pixel. Otherwise $ML(n,m)$ is assigned 0 for a black pixel. Since the ML region estimate assigns pixels to black and white without regard to the assignments of adjacent pixels, this algorithm produces a number of false assignments and a somewhat 'spotty' result.

b. Maximum A Posteriori Region Estimation

The 'maximum a posteriori' (MAP) region estimation utilizes the Markov model to describe the occurrence of regions in the image. The combination of the linear filtering model with the Markov model results in an algorithm to achieve a MAP region estimation. For MAP estimation the regions are considered to be random quantities, and we maximize the probability for a given set of regions conditioned on our observation of the multichannel image. From Bayes rule, the *a posteriori* probability can be written as

$$\Pr[R_1, R_2, \dots, R_q | E] = \frac{p(E | R_1, R_2, \dots, R_q) \cdot \Pr[R_1, R_2, \dots, R_q]}{p(E)} \quad (2.26)$$

Since the denominator of Equation 2.26 does not depend on the regions, *maximum a posteriori* (MAP) estimate for the regions can be obtained if the R_i are chosen to maximize the numerator

$$p(E | R_1, R_2, \dots, R_q) \cdot \Pr[R_1, R_2, \dots, R_q] \quad (2.27)$$

One can define the "state" $s(n,m)$ of point (n,m) as the region type to which that point has been assigned. In our development, the number of region types is assumed to be 2. Since the set of all possible state assignments for points in the image is one-to-one with the set of all possible divisions of the multichannel image into regions, the region estimation problem can be viewed as one of estimating the states of the points. It is assumed that the state of a point is stochastically dependent on some adjacent set of states $S_{n,m}$ in a symmetric support region, as shown in Figure 2.4. Since S represents a chosen set of state assignments for all points in the multichannel

image, $\Pr [S]$ denotes the joint probability that the points in the image take on a chosen set of state assignments. The support set defines a neighborhood structure i.e. all elements in the support set are neighbors of each other. It can be shown that if the set of states S is a Markov random field, then the probability of S can be factored as a product of terms of functions depending only on the "cliques" of the support set $S_{n, m}$. The cliques are defined as groups of points such that each set of points are neighbors of each other according to the support set. For a Markov random field, the probability of S can be written as

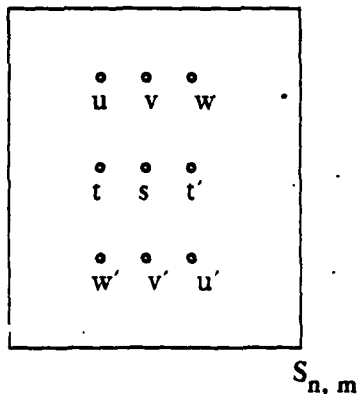


Figure 2.4 State support region of the point s for MAP estimation.

$$\Pr [S] = \prod_{(n,m)} \Pr [s(n,m) | S_{n, m}] \quad (2.28)$$

where the terms in the product are additive functions defined on the cliques of $S_{n, m}$ and the product is over all cliques in S . One simple acceptable form for the terms in the product is

$$\Pr [s(n,m) | S_{n, m}] = \frac{1}{D} \exp [s(n,m) \{ \alpha + \beta_1 (t+t') + \beta_2 (v+v') + \gamma_1 (u+u') + \gamma_2 (w+w') \}] \quad (2.29)$$

where $t = s(n-1,m)$, $t' = s(n+1, m)$, $S_{n, m}$ is the set of states as shown in Figure 2.4, and D is a normalizing constant. One particular selection of the parameters, namely $\alpha = -4$, $\beta_1 = \beta_2 = \gamma_1 = \gamma_2 = 1$, leads to a particularly simple algorithm. In this case, we have

$$\Pr [1 | S_{n, m}] = \frac{1}{D} \exp (\sum_{(i,j) \in S_{n, m}} (s(i, j) - 1 / 2)) \quad (2.30)$$

and

$$\Pr [0 | S_{n, m}] = \frac{1}{D} \quad (2.31)$$

The second term in the numerator of Equation 2.26 can be replaced by $\Pr[S]$. Thus maximizing Equation 2.26 is equivalent to minimizing

$$- 2 \ln p(\underline{E} | R_1, \dots, R_q) - 2 \ln \Pr [S] \quad (2.32)$$

One can define the MAP region estimate by combining Equations 2.22 , 2.26 , 2.28 , and 2.32 as

$$\begin{aligned} \sum_{(n,m)} [\underline{E}^1 (n,m)]^T [\Sigma_w^1]^{-1} [\underline{E}^1 (n,m)] \\ + \ln | \Sigma_w^1 | - 2 \ln \Pr [1 | S_{n, m}] & \begin{matrix} 0 \\ < \\ 1 \end{matrix} \\ \sum_{(n,m)} [\underline{E}^0 (n,m)]^T [\Sigma_w^0]^{-1} [\underline{E}^0 (n,m)] \\ + \ln | \Sigma_w^0 | - 2 \ln \Pr [0 | S_{n, m}] & \end{aligned} \quad (2.33)$$

For $\Pr [h | S_{n, m}]$ in the form of Equation 2.30 and Equation 2.31 computing the terms $- 2 \ln \Pr [h | S_{n, m}]$ is equivalent to counting the number of pixels in $S_{n, m}$ that have value 'h' and dividing by the total number of pixels in $S_{n, m}$, and multiplying by an appropriate normalizing factor, KS.¹ A larger state support region $S_{n, m}$ is depicted in Figure 2.5 as an example. The side of the $S_{n, m}$ must be an *odd* number. Although it does not necessarily lead to the true MAP estimate we find it convenient in practice to maximize Equation 2.33 term by term. That is, we require to use Equation 2.33 without sum. Equation 2.33 can be solved by iteration using the maximum likelihood

¹The normalizing factor results because the quantities α , β_1 , β_2 , γ_1 , and γ_2 in Equation 2.29 can be scaled arbitrarily and still result in a legitimate probability function.

state estimates obtained from Equation 2.24 as an initial set of states for MAP region estimate.

0	1	0	1	1
1	0	1	1	0
1	1	S	1	0
1	0	1	1	1
0	0	1	0	0

Figure 2.5 A Set of States 1's, 0's adjacent to S for MAP Region Estimate.

The computational requirements of the MAP region estimation are reduced by storing the differences,

$$MLD(n,m) = ML_1(n,m) - ML_0(n,m) \quad (2.34)$$

incurred during the calculation of the ML region estimate. Substituting Equation 2.34 in Equation 2.33 gives

$$MLD(n,m) - 2 \ln \Pr [1 | S_{n,m}] + 2 \ln \Pr [0 | S_{n,m}] \begin{matrix} < 0 \\ > 0 \\ = 0 \end{matrix} \quad (2.35)$$

At each iteration terms $\Pr [h | S_{n,m}]$ are evaluated based on the values of the states at the previous iteration. For our particular method of selecting $\Pr [h | S_{n,m}]$, Equation 2.35 can be expressed as

$$MLD(n,m) - KS \left| \frac{2 (\text{number of state 1 pixels}) - (\text{number of pixels in } S_{n,m}) + 1}{\text{number of pixels in } S_{n,m}} \right| \begin{matrix} < 0 \\ > 0 \\ = 0 \end{matrix} \quad (2.36)$$

There are two important points in Equation 2.36 in order to perform the maximum a posteriori image segmentation accurately. The value of the convergence factor, KS , must be assigned properly. If KS is assigned too small, the segmentation may not remove improperly classified pixels. On the other hand, if KS is assigned too large, correctly classified pixels could be changed. In addition, the size of $S_{n,m}$ must be large enough. Otherwise, false assignments produced by the initial ML segmentation may not be removed.

III. KARHUNEN-LOËVE TRANSFORMATION AND ONE-CHANNEL IMAGE SEGMENTATION

In this chapter, the models and relevant algorithms are presented to perform the Karhunen-Loève (K-L) transformation [Ref. 3] and one-channel image segmentation utilizing the techniques of linear prediction [Ref. 1]. Since linear prediction techniques are presented in detail for multichannel image segmentation in the previous chapter, this discussion concentrates on the K-L transformation. The K-L model and algorithm are first developed to reduce the three-channel color problem to a one-channel problem. Then, a one-channel segmentation procedure is presented that is based on the same model previously discussed. The results of the K-L transformed one-channel image segmentation are presented and compared with the multichannel image segmentation in Chapter IV.

A. MODEL DEVELOPMENT

The K-L transformation developed in this section is based on the statistical properties of an image. This transformation provides an energy compaction between channels of a color image. That is, most of the color image energy is compacted into one channel, and the transformed image channels are uncorrelated. If the multichannel image and transformed multichannel image are expressed in vector form, The K-L transformation is given by [Ref. 7]

$$\underline{Q}(n, m) = [\underline{A}] \underline{E}(n, m) \quad (3.1)$$

where $\underline{E}(n, m)$ is the original multichannel image, $\underline{Q}(n, m)$ is the transformed multichannel image, and \underline{A} is the K-L transformation matrix, whose rows are eigenvectors of the between-channel correlation matrix \underline{R} defined by

$$\underline{R} = E[\underline{E}(n, m) \underline{E}^T(n, m)]. \quad (3.2)$$

The between-channel correlation matrix of the transformed image is

$$\begin{aligned} \underline{\Lambda} &= E[\underline{Q}(n, m) \underline{Q}^T(n, m)] \\ &= [\underline{A}][\underline{R}][\underline{A}]^{-1} \end{aligned} \quad (3.3)$$

where the matrix Λ is a diagonal matrix of the form

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} \quad (3.4)$$

and the λ_k represent eigenvalues of the between-channel correlation matrix. The eigenvalues are ordered such that

$$\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0 \quad (3.5)$$

The importance of this property is that each eigenvalue λ_k is equal to the variance of the k^{th} channel of the transformed multichannel image whose channels are uncorrelated. Then, it is a well known property of multivariate statistics that the total variability of the color image has the form [Ref. 3]

$$\lambda_T = \sum_{k=1}^3 \lambda_k \quad (3.6)$$

which relates the total variability to the decorrelated component variations, λ_k . One can observe that often the λ_k values have a wide range of magnitudes, and the first component, λ_1 , will be sufficient to approximate λ_T with only a small percentage of error. This becomes the key idea for the use of the K-L transformation. Table 1 shows the energy distribution between the transformed color image channels of two test images.

Indeed, in a 3-channel image one can often find that the first channel of the K-L transformed image is sufficient to account for 99 percent of all the variability. That is, it is typical to find that

$$\lambda_1 = 0.99 \lambda_T \quad (3.7)$$

The Karhunen-Loève transformation provides the best energy compaction [Ref. 8] and the advantage of this transformation is computational savings. We will see later that

TABLE 1
ENERGY DISTRIBUTION BETWEEN TRANSFORMED IMAGE CHANNELS

	Percentage of Energy in Channels		
	Q_1	Q_2	Q_3
Image 1	99.13	0.84	0.03
Image 2	99.15	0.78	0.07

one-channel image segmentation achieved by processing only the first channel of the K-L transformed color image will be very close to the result obtained on the original image with a multichannel algorithm, but will be obtained at only one ninth of the computational cost.

B. ALGORITHM DEVELOPMENT

In this section, the algorithm to perform K-L transformation of color images is presented. Since the K-L transformation is based upon the between-channel correlation matrix, R , of the color image, the between-channel correlation matrix is first determined. Then the eigenvectors of the between-channel correlation matrix are computed. Finally, the K-L transformation is formulated using the transpose of the eigenvector matrix.

1. Correlation Function Estimation

In order to determine the K-L transformation of Equation 3.1, the between-channel correlation matrix of the color image must first be estimated. Our estimate for the between-channel correlation matrix is given by

$$R = \frac{1}{N^2} \sum_{n=0}^{N-1} \sum_{m=0}^{N-1} F(n, m) (F(n, m))^T \quad (3.8)$$

where the image size is N by N , and the between-channel correlation matrix size is K by K .

2. Karhunen-Loeve Transformation Matrix

Since the rows of the K-L transformation matrix are the eigenvectors, E , of the between-channel correlation matrix, the eigenvectors must be calculated from the between-channel correlation matrix of the color image. The K-L transformation matrix is then obtained using the transpose of the eigenvector matrix. That is

$$[A] = \begin{bmatrix} \leftarrow e_1^T \rightarrow \\ \leftarrow e_2^T \rightarrow \\ \leftarrow e_3^T \rightarrow \end{bmatrix} \quad (3.9)$$

3. Karhunen-Loeve Transformation

Since the K-L transformation matrix satisfies Equation 3.3, then the K-L transformation is represented by Equation 3.1 with A is given by Equation 3.9, where e_i^T , $i = 1, 2, 3$ are the eigenvectors of R . More explicitly, the components of Q are determined from the components of F at any pixel (n, m) as

$$\begin{bmatrix} Q_1(n, m) \\ Q_2(n, m) \\ Q_3(n, m) \end{bmatrix} = \begin{bmatrix} \leftarrow e_1^T \rightarrow \\ \leftarrow e_2^T \rightarrow \\ \leftarrow e_3^T \rightarrow \end{bmatrix} \begin{bmatrix} F_1(n, m) \\ F_2(n, m) \\ F_3(n, m) \end{bmatrix} \quad (3.10)$$

C. ONE-CHANNEL IMAGE SEGMENTATION

The one-channel segmentation procedures presented in this section are based on the same model that was described in detail for the multichannel image in Chapter II. A single channel image is used instead of a three channel image. That is, K is always equal to 1 in the Equations of Chapter II. As a result the vector and matrix quantities become scalars and the equations are simplified.

In order to model the single image by Equations 2.2 and 2.3, the mean of the image is estimated using the Equation 2.11. Then the correlation function is estimated in the same manner as in Section II-B.b where $R(i, j)$ is a scalar instead of a matrix. This procedure is followed by estimation of the filter coefficients and the prediction error covariance. The equations in Section II-B.c are then used to determine the filter

coefficients, A_{ij} , and the prediction error covariance, Σ_w , now a scalar value. Finally, the one-channel segmentation algorithm is applied. The method is the same as that described in detail for the color images in Section II-B.2. However, instead of Equation 2.24 and 2.33 the following simplified relations are used for the maximum likelihood and the maximum a posteriori region estimates. A maximum likelihood region estimate for a single channel image of the pixel is given by [Ref. 1]

$$\frac{(E^1(n,m))^2}{\Sigma_w^1} + \ln(\Sigma_w^1) \stackrel{0}{>} \frac{(E^0(n,m))^2}{\Sigma_w^0} + \ln(\Sigma_w^0) \quad (3.11)$$

and the maximum a posteriori region estimate is given by

$$\begin{aligned} & \frac{(E^1(n,m))^2}{\Sigma_w^1} + \ln(\Sigma_w^1) - 2 \ln \Pr[1 | S_{n,m}] \\ & \stackrel{0}{>} \frac{(E^0(n,m))^2}{\Sigma_w^0} + \ln(\Sigma_w^0) - 2 \ln \Pr[0 | S_{n,m}] \end{aligned} \quad (3.12)$$

where E^1 and E^0 are the result of applying the linear predictive filters to the first channel of the K-L test image.

IV. RESULTS AND COMPARISON OF THE METHODS

In this chapter, the results of the multichannel image segmentation, the Karhunen-Loève transformed one-channel image segmentation, and the K-L transformed 3-channel image segmentation are presented and compared.

The digitized image size used in this work is 128 by 128 pixels with gray levels represented on a scale of 0 to 255 (8 bits). A digitized color photograph of a rural area containing trees (the green region) and fields (the yellow region) are shown in Figure 4.1. A quarter-plane filter for each texture class (2×2 pixels) was designed and applied to the color image to achieve the multichannel image segmentation. A state support region of 7 by 7 pixels was used for MAP region estimation. The results of the maximum likelihood (ML) and the maximum a posteriori (MAP) segmentations of Figure 4.1 image are shown in Figures 4.2 and 4.3 respectively. The segmentation results show the field regions as black and tree regions coded as white. The ML result (Fig 4.2) is spotty, but the true tree and field regions are distinguishable. The MAP segmentation result (Fig 4.3) of Figure 4.1 image is quite clear. The MAP segmentation was not able to remove a few improperly classified points in the left side of the field region. Since there is an inherent ambiguity in the estimation of the region boundaries due to the finite size of the masks, the edges are expectedly somewhat rough. Figure 4.4 shows another color image of a rural area containing trees and fields. Figures 4.5 and 4.6 show the results of the ML and the MAP segmentation of the Figure 4.4 image. The ML estimation was achieved using the filters designed for the image of Figure 4.1. The result of the ML segmentation (Fig 4.5) is again quite spotty, i.e. Although two regions are discernible. The MAP algorithms segmented the regions quite accurately as shown in Figure 4.6. The MAP estimates presented above converged after 10 iterations and KS was assigned to 100.

In the results presented above the ML procedure produced a poor result with a lot of false regions. This is due to the lack of prior information about region connectivity. On the other hand, MAP estimation using the Markov model to represent region transitions produced results that was quite accurate.

Figure 4.7 shows the first channel of the Karhunen-Loève (K-L) transformed image of the Figure 4.1. The image size is 128 by 128 pixels with the scaled gray levels

within the intensity range of the display. The result of the one-channel ML segmentation of Figure 4.7 is depicted in Figure 4.8 . The one-channel ML segmentation result is quite spotty, but the two regions are perceptually discernible. On the other hand, the MAP segmentation result (Fig 4.9) of Figure 4.7 is quite smooth, although there are a few incorrectly classified points in both regions.

The first channel of the Karhunen-Loève transformed image of Figure 4.4 is shown in Figure 4.10 , and Figures 4.11 and 4.12 show the results of the one-channel ML and MAP segmentations of Figure 4.10 respectively. The one-channel ML segmentation result (Fig 4.11) has a lot of spots, but both segmented regions are distinguishable. The maximum a posteriori segmentation (Fig 4.12) of Figure 4.10 is quite smooth, but again there are a few incorrectly classified sets of pixels in both regions.

The results of multichannel image segmentation and the Karhunen-Loève transformed one-channel image segmentations were presented consecutively. These results show that the ML estimation of the Karhunen-Loève transformed single channel image is much more spotty than the ML estimation of the multichannel image. But, the MAP estimation results of the K-L transformed single channel images are as clear as the MAP segmentation results of the multichannel images.

In summary the results presented in this chapter show that the best segmentation result is provided by the multichannel image segmentation method. However the segmentation results of the Karhunen-Loève transformed single channel images are very close to multichannel image segmentation results, i.e. Because most of the color image energy (99 percent) is compacted into the first channel.



Figure 4.1 Two-Texture Color Image.



Figure 4.2 ML Region Estimation of Figure 4.1 Image.



Figure 4.3 MAP Region Estimation of Figure 4.1 Image.

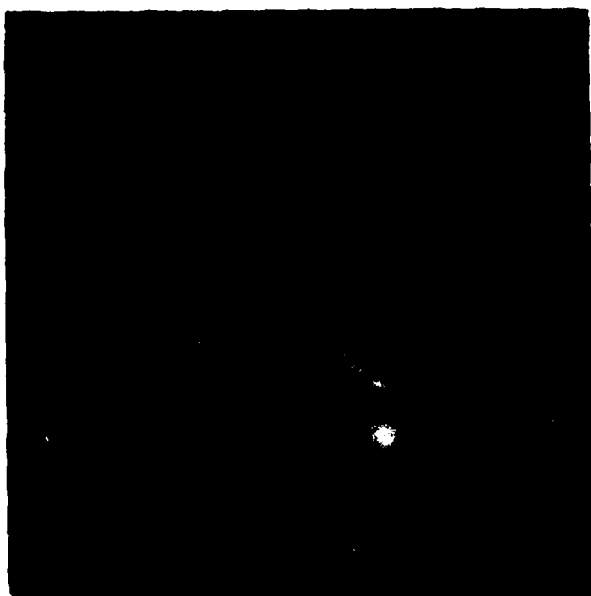


Figure 4.4 Color Image Containing Two-Texture.



Figure 4.5 ML Region Estimation of Figure 4.4 Image.



Figure 4.6 MAP Region Estimation of Figure 4.4 Image.

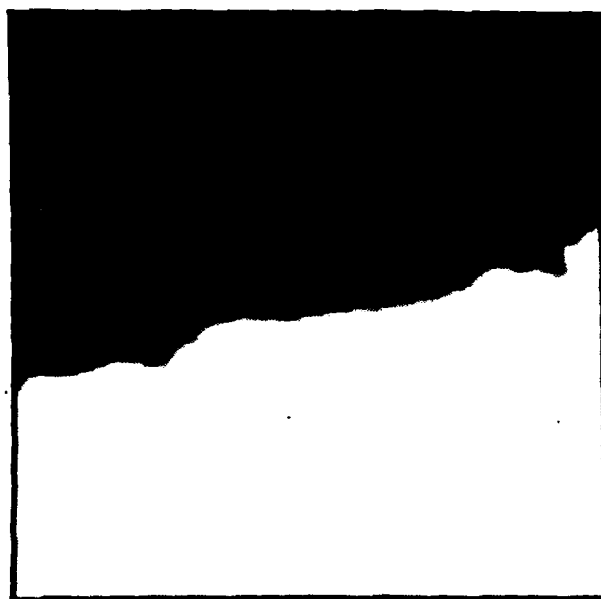


Figure 4.7 First Channel of K-L Transformation of Figure 4.1 Image.

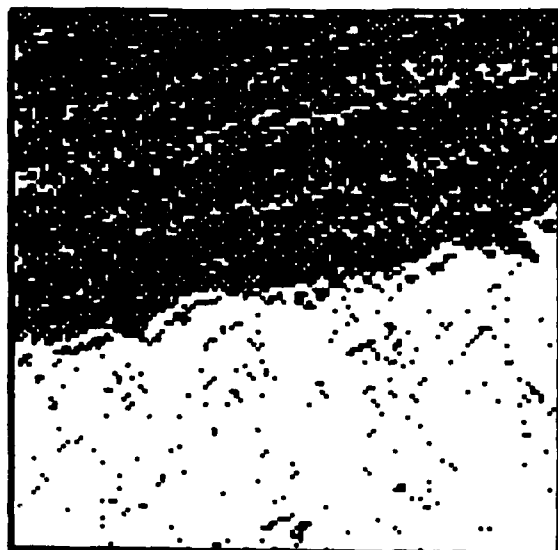


Figure 4.8 ML Region Estimation of Figure 4.7.

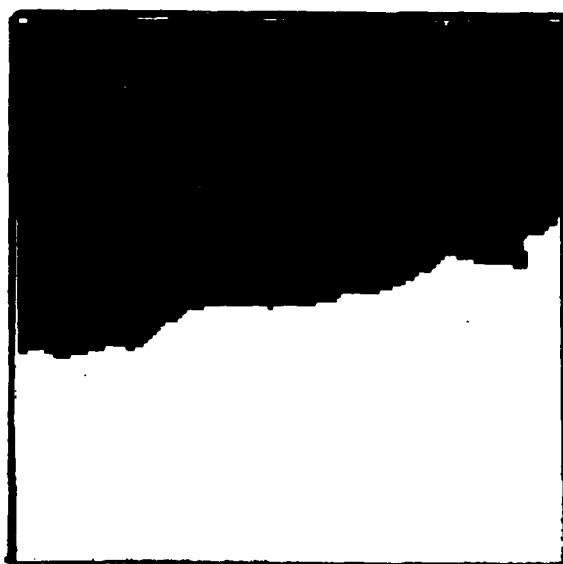


Figure 4.9 MAP Region Estimation of Figure 4.7.



Figure 4.10 K-L Transformed Single Channel Image of Figure 4.4.

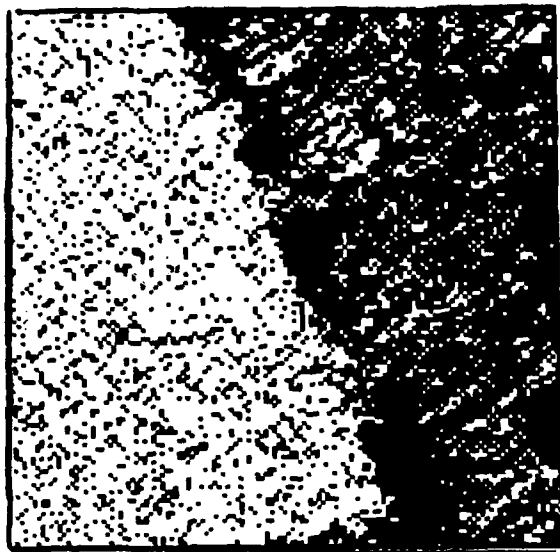


Figure 4.11 ML Segmentation of Figure 4.10.



Figure 4.12 MAP Segmentation of Figure 4.10.

V. CONCLUSIONS

The segmentation of terrain images is an important part of image analysis methods for military and civilian applications. The work in this thesis utilized a 2-D stochastic linear filtering model and compared algorithms for multichannel image segmentation of color images. Two levels of structure were used for multichannel segmentation development. The fundamental structure based on the linear filtering concepts represents the texture in local regions of terrain. Superimposed on this structure is a Markov random field that describes transitions from one region type to another. The segmentation was considered as a region estimation problem and maximum likelihood and maximum a posteriori region estimation methods were developed. The ML region estimation produced a spotty result, but the MAP region estimation produced quite accurate results for the multichannel and single channel image.

The other piece of work developed in this thesis was the Karhunen-Loève transformation model that based on the statistical characteristics of color image. The one-channel image segmentation was then applied to the first channel of the Karhunen-Loève transformed color image to see the effectiveness of the K-L transformation for segmentation.

We observed that multichannel image segmentation results were quite accurate. Similarly the results of the K-L transformed one-channel image segmentation were very smooth. In summary the results of both segmentation methods were very close to each other, and the K-L transformation is very effective for segmentation.

APPENDIX A RELAXATION METHOD

The Relaxation Method algorithm utilizes a set of iterative numerical techniques to compute a posterior probability of the pixel (n,m) from a prior probability of the same pixel and a set of prior probabilities of the adjacent pixels. The prior probabilities are estimated from a 2-D image data using the linear filtering model (see Equation 2.25).

The Relaxation formula is defined [Ref. 9] by

$$P_{ij}^{k+1}(n,m) = \text{Avg}_S \left(\frac{\lambda_{ij}^s P_{ij}^k(n,m)}{\sum_{t=1}^T \lambda_{it}^s P_{it}^k(n,m)} \right) \quad (\text{A.1})$$

where k is the number of the iteration, λ_{ij}^s is the relaxation factor, $P_{ij}^k(n,m)$ are a set of prior probabilities, T is the number of textures, and S is the number of pixels. The updated estimates $P_{ij}^{k+1}(n,m)$ are obtained by averaging all of the terms in parentheses. The relaxation factor, λ_{ij}^s , in Equation A.1 is given by

$$\lambda_{ij}^s = \sum_{t=1}^T c(i,j | s,t) P_{st}^k(n,m) \quad (\text{A.2})$$

where $c(i,j|s,t)$ is a nonnegative compatibility function whose value is small if the neighboring pixel is black when the estimated pixel is white, otherwise its value will be large. λ_{ij}^s is used to update the probability $P_{ij}^k(n,m)$. Note that λ_{ij}^s is large if the compatibilities $c(i,j|s,t)$ are large and the probabilities P_{st}^k are high, otherwise λ_{ij}^s will be small.

The results of the Relaxation Method segmentation are shown in Figures A.1 and A.2. The Figure A.1 presents the segmentation of Figure 4.7 with the compatibility $c(i,x|s,x)$ is equal to 0.1, where x can be 0 or 1. The result is very spotty but both regions are discernable. The Figure A.2 gives the segmentation with the compatibility $c(i,x|s,x)$ is equal to 0.9. This result is better than the previous result, but there are still several spots especially in the field region. Both results are obtained after

10 iterations. Figure 4.9 shows the result of MAP segmentation of Figure 4.7 . The MAP segmentation result is much more accurate than the Relaxation method segmentation.

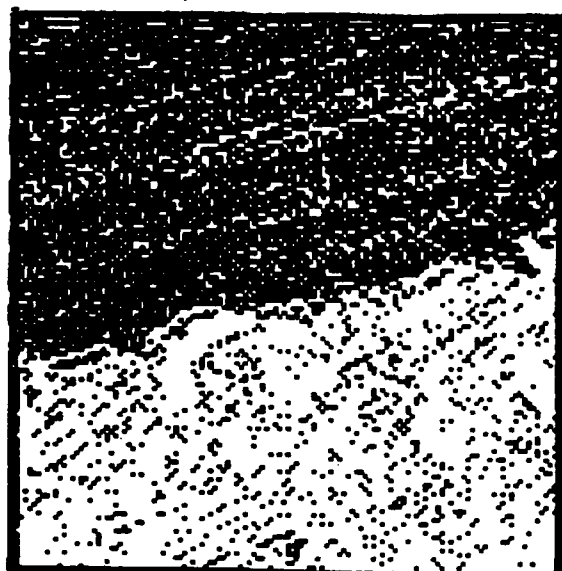


Figure A.1 Relaxation Method Segmentation with $c = 0.1$.

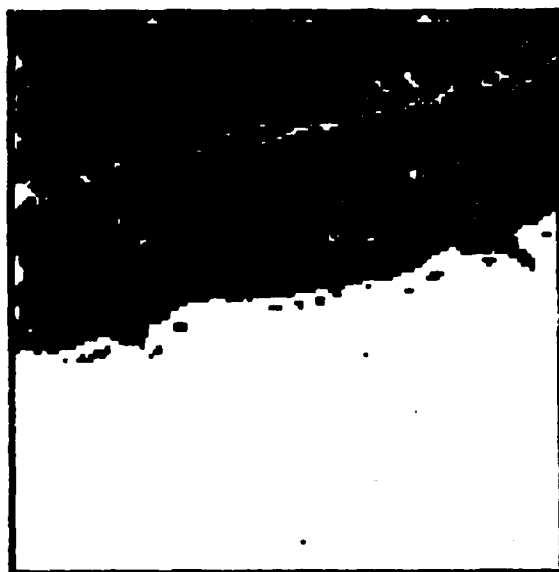


Figure A.2 Relaxation Method Result with $c = 0.9$.

APPENDIX B

FILTER PARAMETER ESTIMATION AND MULTICHANNEL SEGMENTATION

The interactive program, FLTR1, estimates two sets of filter parameters from a 2-D three-channel image. The corresponding algorithms were presented in Section II.B.1. In order to run this program, the user must input the required program parameters in the order listed below

- * The number of filter rows, P. Maximum is 4.
- * The number of filter columns, Q. Maximum is 4.
- * The number of rows, N, in each image channel. Maximum is 128.
- * The number of columns, M, in each image channel. Maximum is 128.
- * The number of channels, K, in image.
- * The filenames of the image channels.
- * The coordinates of the estimation windows of textures.
- * Two output filenames for the estimated filter parameters.

The mean vectors of the data in the two estimation windows is first computed by FLTR1. Then, the program subtracts the mean from the image and determines the correlation functions. After calculating the correlation matrix, the program determines the covariance matrix, Σ , using the equation

$$[R][B] = [S_I] \quad (B.1)$$

where B is a dummy matrix that has the same dimension with A matrix, $B_{00} = [\Sigma_w]^{-1}$ and S_I is all zero except for an identity matrix in its first partition. The covariance matrix must satisfy the relation

$$B_{00} \cdot \Sigma_w = I \quad (B.2)$$

Finally, the filter weighting coefficients are estimated using

$$[A] = [B] \cdot [\Sigma] \quad (B.3)$$

MULTICHANNEL IMAGE SEGMENTATION PROGRAM

The interactive program, SGMT1, segments a color image with two textures when given the three-channel image, the image dimension, and two sets of filter parameters. Again, the user must input the required program parameters to run the program. These parameters have to be in the order listed below :

- * The number of rows, N, in the image channels.
- * The number of columns, M, in the image channels.
- * The number of filter rows, P.
- * The number of filter columns, Q.
- * The number of textures, T, in the image.
- * The number of channels, K, in the image.
- * The filenames of the image channels.
- * The filenames of the filter parameters.
- * The output filename of the ML segmentation.
- * The output filename of the MAP segmentation.

This program estimates the errors of two textures using Equation 2.7, then performs the ML segmentation and the MAP segmentation using Equations 2.25 and 2.33 . The convergence factor KS, and the size of $S_{n, m}$ must be assigned properly by user to perform the MAP segmentation accurately.

APPENDIX C

KARHUNEN-LOËVE TRANSFORMATION

The interactive program, **KRLV**, implements the Karhunen-Loève transformation algorithms described in Section III.B. This program requires the user to assign the program parameters in the order listed below :

- * The number of channels, **K**, in the image.
- * The number of rows and columns, **N**, in each channel.
- * The filenames of the image channels.
- * The output filenames of the transformed color channels.

The correlation matrix is first calculated. Then the program calls the **IMSL** subroutine **EIGRS** to calculate the eigenvalues and the eigenvectors of the correlation matrix. Finally, the transformed color image is obtained by multiplying the transpose of the eigenvectors matrix by the original color image. The program scales the transformed color image for display on the **COMTAL** image processing system.

ONE-CHANNEL IMAGE SEGMENTATION PROGRAM

The program, **FLTR2**, calculates two sets of filter parameters from a 2-D single channel image. The user must input the required program parameters to run the program. These parameters except the number of channel, **K**, are given in Appendix B.

The program, **SGMT2**, implements a single channel image segmentation. The required program parameters given in Appendix B have to be assigned to run the program. Equations 3.11 and 3.12 are used to perform the **ML** region estimation and the **MAP** region estimation.

APPENDIX D COMPUTER PROGRAMS FOR MULTICHANNEL IMAGE SEGMENTATION

```

C *****
C *
C * PROGRAM FLTR1
C *
C * PURPOSE To develop two sets of filter parameters from a 2-D
C * three-channel input image. These parameters are the
C * mean vector, the covariance, and the filter coefficients
C * of the image.
C *
C * REQUIRED IMSL ROUTINES
C *
C * LEQT2F, LUDATN, LUELMN, LUREFN
C *
C * IMPLEMENTED BY LTJG TIMUR KUPELI Nov 1986
C *
C *****
C
C *** VARIABLE DEFINITIONS ***
C
C BINPUT = [ Input ] Image data in byte format.
C FINPUT = [ Input ] image data in real*4 format.
C P , O = Rows, Columns of the linear filter.
C N , M = Rows, Columns of the image data.
C K = The number of channels in image.
C T = The number of filters for processing.
C IMAGE = [ Input ] Filename of the image channels.
C FILTER = [ Output ] Filename of the filter parameters.
C MEAN = Array of mean vectors of estimation windows.
C R = The correlation matrix.
C IMATRX = Identity matrix.
C KW = The covariance matrix.
C A = The filter coefficients matrix.
C ISIZE = The estimation window size.
C NO, MO = Row, column delay(shift) of correlation.
C
C This program uses 2 by 2 pixels filter. If user wants to use
C different size filter, the dimensions of the following
C variables must be modified.
C R, SI, A, WAREA
C For example, for 4 by 4 pixels filter, the dimensions must be
C R(48,48), SI(48,3), A(48,3), WKAREA(2448)
C
C INTEGER*4 P,O,ROW,COL,STARTN(2),STARTM(2),ENDN(2),ENDM(2),
C RNRW,RNCOL,RRW,CCOL,X,Y,K,IER,OK,PKO,L,J,JJ,JJJ,
C HNNO,HMMO,HCOL,HROW,LNNO,LNMO,LCOL,LROW,RN,RM,T,
C NO,MO,RRN,RRM,ROW1,COL1,MMO,NNO,IDGT,I
C
C REAL*4 SUM,TEMP,FINPUT(128,128,3),MEAN(2,3),WKAREA(180),
C R(12,12),SI(12,3),IMATRX(3,3),B00(3,3),SUM1,SUM2,SUM3,
C KW(3,3),A(12,3),ISIZE
C
C CHARACTER*50 IMAGE(3),FILTER(2)
C
C BYTE BINPUT(128)
C
C T = 2
C
C GET PROGRAM INPUT PARAMETERS.

```

```

C
10  TYPE 10
    FORMAT(' ENTER NUMBER OF FILTER ROWS FROM 2-4 DESIRED :', $)
    READ 11, P
11  FORMAT(I3)
C
12  TYPE 12
    FORMAT(' ENTER NUMBER OF FILTER COLUMNS FROM 2-4 DESIRED :', $)
    READ 11, Q
C
13  TYPE 13
    FORMAT(' ENTER NUMBER OF ROWS IN IMAGE ', $)
    READ 11, N
C
14  TYPE 14
    FORMAT(' ENTER NUMBER OF COLUMNS IN IMAGE ', $)
    READ 11, M
C
15  TYPE 15
    FORMAT(' ENTER NUMBER OF CHANNELS [ MAX = 3 ] IN IMAGE ;', $)
    READ(*, 11) K
C
    GET THE MULTICHANNEL IMAGE
C
    DO 16 J = 1 , K
C
        WRITE(*, 17) J
17        FORMAT(' ENTER FILENAME OF IMAGE CHANNEL ' I3, $)
        READ(*, 18) IMAGE(J)
18        FORMAT(A50)
C
    CONVERT THE IMAGE FROM BYTE FORMAT TO REAL*4 FORMAT
C
    OPEN(UNIT=1, FILE=IMAGE(J), STATUS='OLD', ACCESS = 'DIRECT')
C
    DO 180 ROW = 1 , N
        READ (1, 'ROW) (BINPUT(COL), COL=1, M)
        DO 181 COL = 1 , M
            TEMP = BINPUT(COL)
            IF (TEMP.LT.0.0) THEN
                TEMP = TEMP + 256
            END IF
            FINPUT(ROW, COL, J) = TEMP
181        CONTINUE
180    CONTINUE
        CLOSE (UNIT=1)
C
16    CONTINUE
C
    GET 'T' AREAS FOR WHICH FILTERS ARE DESIRED AND OUTPUT FILENAMES
    FOR EACH AREA'S FILTER COEFFICIENTS AND COVARIANCE MATRIX.
C
    DO 19 I = 1, T
        WRITE(*, 20) I
20        FORMAT(' ENTER UPPER-LEFT ROW FOR AREA ', I2, ':', $)
        READ(*, 11) STARTN(I)
C
        WRITE(*, 21) I
21        FORMAT(' ENTER UPPER-LEFT COLUMN FOR AREA ', I2, ':', $)
        READ(*, 11) STARTM(I)
C
        WRITE(*, 22) I
22        FORMAT(' ENTER LOWER-RIGHT ROW FOR AREA ', I2, ':', $)
        READ(*, 11) ENDN(I)
C
        WRITE(*, 23) I
23        FORMAT(' ENTER LOWER-RIGTH COLUMN FOR AREA ', I2, ':', $)
        READ(*, 11) ENDM(I)
C

```

```

24      WRITE(*,24) I
        FORMAT(' ENTER OUTPUT FILE-SPEC FOR FILTER',I2,',',',',$',
              READ(*,18) FILTER(I)

C
C
C
FIND THE MEAN VECTOR OF ESTIMATION WINDOW , T, AREAS OF IMAGE
CHANNELS. THE MEAN VECTOR CONSISTS OF THE MEAN FOUND EACH CHANNEL

        ISIZE = (ENDN(I) - STARTN(I) + 1)*(ENDM(I) - STARTM(I) + 1)
        SUM1 = 0.0
        SUM2 = 0.0
        SUM3 = 0.0
        DO 25 L = STARTN(I),ENDN(I)
          DO 26 J = STARTM(I),ENDM(I)
            SUM1 = SUM1 + FINPUT(L,J,1)
            SUM2 = SUM2 + FINPUT(L,J,2)
            SUM3 = SUM3 + FINPUT(L,J,3)
          CONTINUE
        CONTINUE
26      MEAN(I,1) = SUM1 / ISIZE
25      MEAN(I,2) = SUM2 / ISIZE
        MEAN(I,3) = SUM3 / ISIZE
        WRITE(*,27) (MEAN(I,II),II=1,K)
27      FORMAT(' MEAN:',3F9.3,$)

C
C
C
        CORRECT THE IMAGE TO BE ZERO MEAN

        DO 271 J = 1, K
          DO 28 L = STARTN(I), ENDN(I)
            DO 29 LL = STARTM(I),ENDM(I)
              FINPUT(L,LL,J) = FINPUT(L,LL,J) - MEAN(I,J)
            CONTINUE
          CONTINUE
        CONTINUE
28      CONTINUE
271    CONTINUE

C
C
C
        DETERMINE THE 2-D CORRELATION FUNCTION OF THE IMAGE CHANNEL.
        THE CORRELATION MATRIX APPROPRIATE TO THE INPUT INPUT PARAMETERS
        OF P, K, Q

        WRITE(*,291) I
291      FORMAT(' CORRELATION.MATRIX',I2,$)
        PKQ = P * K * Q
        OK = Q * K
        DO 30 RNROW = 1,P
          X = OK * (RNROW-1)
          DO 31 RNCOL = 1,P
            NO = RNROW - RNCOL
            Y = OK * (RNCOL-1)
            DO 32 RMROW = 1,Q
              RN = K * (RMROW - 1) + X
              DO 33 RMCOL = 1,Q
                MO = RMROW - RMCOL
                RM = K * (RMCOL - 1) + Y

C
C
C
                LNNO = STARTN(I) + NO
                LMNO = STARTM(I) + MO
                HNNO = ENDN(I) + NO
                HMNO = ENDM(I) + MO

C
C
C
                LCOL = MAXO(STARTM(I),LMNO)
                HCOL = MINO(ENDM(I),HMNO)
                LROW = MAXO(STARTN(I),LNNO)
                HROW = MINO(ENDN(I),HNNO)

        DO 133 ROW1= 1, 3
          RRN = RN + ROW1
          DO 233 COL1 = 1, 3
            RRM = RM + COL1
            SUM = 0.0
            DO 333 ROW = LROW, HROW

```

```

      NNO = ROW - NO
      IF (NNO .LT. LROW) THEN
        RROW = MAX0(ROW,NNO)
      ELSE IF (NNO .GT. HROW) THEN
        RROW = MIN(ROW,NNO)
      ELSE
        RROW = NNO
      END IF

C
      DO 433 COL = LCOL , HCOL
        MMO = COL - MO
        IF (MMO .LT. LCOL) THEN
          CCOL = MAX0(MMO,COL)
        ELSE IF (MMO .GT. HCOL) THEN
          CCOL = MIN0(MMO,COL)
        ELSE
          CCOL = MMO
        END IF

C
      SUM = SUM + FINPUT(ROW,COL,ROW1) * FINPUTSAVEW,CCOL,COL1)
C
      433      CONTINUE
      333      CONTINUE
      R(RRN,RRM) = SUM / ISIZE
      233      CONTINUE
      133      CONTINUE
C
      33      CONTINUE
      32      CONTINUE
      31      CONTINUE
      30      CONTINUE
C
      THE FOLLOWING FORMAT MUST BE MODIFIED TO USE DIFFERENT FILTER SIZE
      THEN 2 by 2 PIXELS.
C
      DO 330 L = 1 , PKQ
        WRITE(*,331) (R(L,J),J=1,PKQ)
        WRITE(*,332)
        331      FORMAT(' ',12F6.0)
        332      FORMAT(' ')
        330      CONTINUE
C
      RESET THE IDENTITY MATRIX.
C
      DO 36 J = 1 , K
        DO 37 L = 1 , K
          IF (J.EQ.L) THEN
            IMATRX(J,L) = 1.0
          ELSE
            IMATRX(J,L) = 0.0
          END IF
        37      CONTINUE
      36      CONTINUE
C
      RESET SI(J,L) TO HAVE [ I ] IN FIRST PARTITION AND [ 0 ] IN ALL OTHERS
C
      DO 38 J = 1 , PKQ
        DO 39 L = 1 , K
          IF (J.EQ.L) THEN
            SI(J,L) = 1.0
          ELSE
            SI(J,L) = 0.0
          END IF
        39      CONTINUE
      38      CONTINUE
C
      SOLVE EQUATION [ R ] * [ B ] = [ SI ] . NOTE THAT THE BELOW
      CALL TO IMSL ROUTINE LEQT2F, [ B ] RETURNS IN [ SI ]
C

```

```

C      IDG = 3
C      CALL LEQT2F (R,K,PKQ,PKQ,SI,IDG,WKAREA,IER)
C      SOLVE EQUATION [ B00 ] * [ KW ] = [ I ] FOR COVARIANCE
C      MATRIX [ KW ] AFTER COLLING IMSL ROUTINE LEQT2F, [ KW ]
C      RETURNS IN [ IMATRX ].
C      DO 45 J = 1 , K
C          DO 46 JJ = 1 , K
C              B00(J,JJ) = SI(J,JJ)
46      CONTINUE
45      CONTINUE
C      CALL LEQT2F(B00,K,K,K,IMATRX,IDG,WKAREA,IER)
C      SOLVE FOR THE FILTER COEFFICIENTS , [ A ] = [ B ] * [ KW ] ,
C      WHICH IN THE PROGRAM IS [ A ] = [ SI ] * [ IMATRX ]
C      DO 47 J = 1 , PKQ
C          DO 48 JJ = 1 , K
C              TEMP = 0.0
C              DO 49 JJJ = 1 , K
C                  TEMP = TEMP + SI(J,JJJ) * IMATRX(JJJ,JJ)
49      CONTINUE
48      A(J,JJ) = TEMP
47      CONTINUE
C      WRITE(*,491) ((IMATRX(J,JJ),JJ=1,K),J=1,K)
491      FORMAT(' ',<K>(F6.2,3X))
C      WRITE(*,53) I
53      FORMAT(' ', I2,$)
C      WRITE(*,491) ((A(J,JJ),JJ=1,K),J=1,PKQ)
C      WRITE OUT MEAN, COVARIANCE MATRIX, AND FILTER COEFFICIENTS TO THE
C      USER INPUT FILE.
C      * OPEN (UNIT=2,FILE=FILTER(1),STATUS='NEW',CARRIAGECONTROL='LIST',
C          FORM='FORMATTED')
C      WRITE(2,495) (MEAN(I,J),J=1,K)
495      FORMAT(F10.4)
C      WRITE(2,495) ((IMATRX(J,JJ),JJ=1,K),J=1,K)
C      WRITE(2,495) ((A(J,JJ),JJ=1,K),J=1,PKQ)
C      CLOSE(UNIT=2)
C      19 CONTINUE
55      WRITE(*,55)
55      FORMAT(' THE PROGRAM FLTR1 IS OVER', $)
55      STOP
55      END

```

```

*****
*
*      PROGRAM SGMT1
*
*      PURPOSE To segment a color image with two textures given
*              the image, the image dimensions, the filter dimen-
*              sions, and the two sets of filter parameters to
*              be used.
*
*      REQUIRED IMSL ROUTINES
*              LINV3F, LUDATN, LUELMN
*
*      IMPLEMENTED BY LTJG TIMUR KUPELI  Nov 1986
*****

****      VARIABLE DEFINITIONS      ****

BINPUT = [ Input ] Image data in the byte format.
ML      = [ Output ] The result of ML segmentation in byte format.
MAP     = [ Output ] The result of MAP segmentation in byte format.
FNAME   = [ Input ] Filename of filter parameters set.
IMAGE   = Filename of the image channel.
P , Q   = Rows , Columns of filter.
N , M   = Rows , Columns of image.
K       = Number of channel of image.
KW      = [ Input ] The covariance matrix.
MEAN    = [ Input ] Mean vector of estimation windows.
ERROR   = Prediction error estimation
A       = [ Input ] Filter coefficients matrix.
TEXTURE = Zero-mean image data in real*4 format.
C01     = Number of removed false points in the first texture.
C10     = Number of removed false points in the other texture.
IN , IM = Maximum number of rows and columns in the image.
P1 , Q1 = Maximum number of rows and columns in the filter.
TMAX    = Maximum number of filters for processing.
IK      = Maximum number of channels in image.

*      INTEGER IN,N,IM,P1,P,Q1,Q,TMAX,T,PQ,ROW,COL,I,J,JJ,JJJ,L,LL,KK,
*              LLL,LLLL,COUNT,LI,HI,LJ,HJ,K,PP,QQ,IK,II,III,C01,C10,M
*
*      REAL   KW(1:3,1:3,1:2),MEAN(1:3,1:2),TEMP,SUM1,SUM2,PML11,LN(2),
*              ERROR(1:128,1:128,1:3,1:2),PML1,PML2,PML(1:128,1:128),
*              AREA,KS,A(1:3,1:3,1:2,1:2,1:2),D1,D2,KW1(1:3,1:3),KW2(3,3),
*              EKW1(1,1:3),EKW2(1,1:3),PML22,DD2,TEXTUR(1:128,1:128,3,3),
*              WKAREA(6),AA(1:128,1:128)
*
*      CHARACTER*50  IMAGE(1:3),FNAME(1:2),MLTEST,MAPTEST
*
*      BYTE   BINPUT(1:128,1:128,1:3),ML(1:128,1:128),MAP(1:128,1:128)
*              MLI(1:128,1:128)
*
*      IN = 128
*      IM = 128
*      P1 = 4
*      Q1 = 4
*      TMAX = 2
*      IK = 3
*
*      GET THE INPUT PARAMETERS OF THE PROGRAM
*
1      WRITE(*,2) IN
2      FORMAT(' ENTER THE NUMBER OF ROWS IN IMAGE.LIMIT OF',I3,':', '$')
3      READ(*,3) N
      FORMAT(I3)
      IF((N.LT.1) .OR. (N.GT.IM)) GOTO 1

```

```

4      WRITE(*,5) IM
5      FORMAT(' ENTER THE NUMBER OF COLUMNS IN IMAGE.LIMIT OF',I3,':', '$)
      READ(*,3) M
      IF((M.LT.1) .OR. (M.GT.IM)) GOTO 4
C
6      WRITE(*,7) P1
7      FORMAT(' ENTER THE NUMBER OF ROWS IN FILTER.LIMIT OF',I3,':', '$)
      READ(*,3) P
      IF((P.LT.2) .OR. (P.GT.P1)) GOTO 6
C
8      WRITE(*,9) Q1
9      FORMAT(' ENTER THE NUMBER OF COLUMNS IN FILTER.LIMIT OF',I3,':', '$)
      READ(*,3) Q
      IF((Q.LT.2) .OR. (Q.GT.Q1)) GOTO 8
C
10     WRITE(*,11) TMAX
11     FORMAT(' ENTER NUMBER OF TEXTURES TO PROCESS.LIMIT OF',I3,':', '$)
      READ(*,3) T
      IF((T.LT.2) .OR. (T.GT.TMAX)) GO TO 10
C
12     WRITE(*,13) IK
13     FORMAT(' ENTER THE NUMBER OF IMAGE CHANNELS.LIMIT OF',I3,':', '$)
      READ(*,3) K
      IF((K.LT.1) .OR. (K.GT.IK)) GO TO 12
C
C      GET ALL CHANNELS OF THE IMAGE
C
      DO 19 I = 1 , K
        WRITE(*,20) I
20     FORMAT(' ENTER FILENAME OF THE IMAGE CHANNEL NUMBER',I3,':', '$)
        READ(*,21) IMAGE(I)
21     FORMAT(A50)
C
        OPEN(UNIT=1,FILE=IMAGE(I),STATUS='OLD',ACCESS='DIRECT')
C
        DO 23 ROW = 1 , N
          READ(1,ROW) (BINPUT(ROW,COL,I),COL = 1 , M )
23     CONTINUE
C
        CLOSE( UNIT = 1 )
C
19     CONTINUE
C
C      GET THE FILTER COEFFICIENT,MEAN, AND COVARIANCE MATRICES
C
      DO 25 I=1,T
        WRITE(*,26) I
26     FORMAT('ENTER FILENAME OF FILTER PARAMETERS SET NUMBER',I3,':', '$)
        READ(*,21) FNAME(I)
C
        OPEN(UNIT=2,FILE=FNAME(I),STATUS='OLD',FORM='FORMATTED')
C
        DO 260 J = 1 , K
          READ(2,27) MEAN(J,I)
27     FORMAT(F10.4)
260    CONTINUE
C
        DO 28 J=1,K
          READ(2,27) (KW(J,JJ,I),JJ=1,K)
28     CONTINUE
C
        DO 29 PP=1,P
          DO 30 QQ=1,Q
            DO 31 ROW=1,K
              READ(2,33) (A(ROW,COL,PP,QQ,I),COL=1,K)
33     FORMAT(F10.4)
31     CONTINUE
30     CONTINUE
29     CONTINUE

```



```

32      CLOSE(UNIT=2)
      FORMAT(3(F10.4,3X))
C
25      CONTINUE
C
      GET THE OUTPUT FILENAMES OF THE ML AND MAP SEGMENTATION RESULTS.
C
      READ(*,220) MLTEST
      READ(*,220) MAPTEST
220     FORMAT(A80)
C
      CONVERT A 2-D BYTE INPUT IMAGE DATA ARRAY IN THE RANGE OF -128 TO
      127 THAT REPRESENTS APPROPRIATE INTENSITY LEVELS IN THE RANGE OF
      0 TO 255 .
C
      DO 35 J = 1 , K
      DO 36 ROW = 1 , N
      DO 37 COL = 1 , M
      TEMP = BINPUT(ROW,COL,J)
      IF(TEMP.LT.0.0) THEN
      TEMP = TEMP+256
      END IF
      TEXTUR(ROW,COL,J,1) = TEMP - MEAN(J,1)
      TEXTUR(ROW,COL,J,2) = TEMP - MEAN(J,2)
37      CONTINUE
36     CONTINUE
35     CONTINUE
C
      CALCULATION OF ERROR ESTIMATE FOR TWO TEXTURES
C
      DO 40 I = 1 , T
      DO 41 L = 1 , N
      DO 42 LL = 1 , M
      DO 421 KK = 1 , K
      ERROR(L,LL,KK,I) = 0.0
      DO 43 III = 1 , P
      J = 1 - III
      DO 44 LLL = 1 , Q
      JJJ = LL - LLL
      DO 45 II = 1 , K
      DO 46 JJ = 1 , K
      IF(J.LE.0) J=1
      IF(JJJ.LE.0) JJJ=1
C
      ERROR(L,LL,KK,I)=ERROR(L,LL,KK,I)+A(II,JJ,III,LLL,I)*TEXTUR(J,JJJ,KK,I)
C
46      CONTINUE
45      CONTINUE
44      CONTINUE
43      CONTINUE
421     CONTINUE
42      CONTINUE
41      CONTINUE
40      CONTINUE
C
      DO 47 JJ=1,K
      DO 48 LL=1,K
      KW1(JJ,LL) = KW(JJ,LL,1)
      KW2(JJ,LL) = KW(JJ,LL,2)
48      CONTINUE
47      CONTINUE
C
      D1 = 1.0
      CALL LINV3F(KW1,6,1,K,K,D1,D2,WKAREA,IER)
      DET1 = D1 * 2**D2
      LN(1) = ALOG(DET1)
C
      D1 = 1.0
      CALL LINV3F(KW2,6,1,K,K,D1,DD2,WKAREA,IER)

```

```

      DET2 = D1 * 2**DD2
      LN(2) = ALOG(DET2)
C
C
C      CALCULATION OF MAXIMUM-LIKELIHOOD IMAGE SEGMENTATION
C
C      * OPEN(UNIT=3,FILE=MLTEST,STATUS='NEW',ACCESS='DIRECT',
C        RECL=(IM/4),MAXREC=IN)
C
C      DO 50 ROW = 1, N
C        DO 51 COL = 1, M
C          DO 52 I = 1, K
C            EKW1(1,I) = 0.0
C            EKW2(1,I) = 0.0
C            DO 53 J = 1, K
C              EKW1(1,I) = EKW1(1,I) + ERROR(ROW, COL, J, 1) * KW1(J, I)
C              EKW2(1,I) = EKW2(1,I) + ERROR(ROW, COL, J, 2) * KW2(J, I)
53      CONTINUE
52      CONTINUE
C        PML11 = 0.0
C        PML22 = 0.0
C        DO 54 L = 1, K
C          PML11 = PML11 + EKW1(1, L) * ERROR(ROW, COL, L, 1)
C          PML22 = PML22 + EKW2(1, L) * ERROR(ROW, COL, L, 2)
54      CONTINUE
C        PML1 = 0.0
C        PML2 = 0.0
C        PML1 = PML11 + LN(1)
C        PML2 = PML22 + LN(2)
C
C        ML(ROW, COL) = 0
C        PML(ROW, COL) = PML2 - PML1
C        IF (PML1 .GT. PML2) THEN
C          ML(ROW, COL) = -1
C        END IF
C        MLI(ROW, COL) = ML(ROW, COL)
51      CONTINUE
C
C      WRITE(3,'ROW') (ML(ROW, COL), COL=1, M)
50      CONTINUE
C
C      CLOSE(UNIT=3)
C
C      MAXIMUM A POSTERIORI IMAGE SEGMENTATION
C
C      * OPEN(UNIT=4,FILE=MAPTEST,STATUS='NEW',ACCESS='DIRECT',
C        RECL=(IM/4), MAXREC = IN)
C
C      KS = 10.0
C      C01 = 0
C      C10 = 0
C      DO 600 II = 1, 5
C        DO 60 I = 1, N
C          DO 61 J = 1, M
C            SUM1 = 0.0
C            SUM2 = 0.0
C            LI = I - 3
C            HI = I + 3
C            LJ = J - 3
C            HJ = J + 3
C
C            IF (LI.EQ.0) LI = 1
C            IF (HI.GT.N) HI = N
C            IF (LJ.EQ.0) LJ = 1
C            IF (HJ.GT.M) HJ = M
C
C            AREA = (HI - LI + 1) * (HJ - LJ + 1)
C
C            DO 62 ROW = LI, HI
C              DO 63 COL = LJ, HJ

```

```

63          SUM1 = SUM1 - MLI(ROW,COL)
62          CONTINUE
          CONTINUE
          SUM1 = SUM1 + MLI(I,J)
C          MAP(I,J) = 0
          SUM2 = PML(I,J) - ((KS/AREA)*(2*SUM1-area+1))
          IF(SUM2.LT.0.0) THEN
            MAP(I,J) = -1
          END IF
          MLI(I,J) = MAP(I,J)
C
61          CONTINUE
60          CONTINUE
600         CONTINUE
C
          DO 70 I = 1, N
            DO 71 J = 1, M
              IF(ML(I,J).EQ.0) THEN
                IF(MAP(I,J).NE.ML(I,J)) C01 = C01 + 1
              ELSE
                IF(MAP(I,J).NE.ML(I,J)) C10=C10+1
              END IF
            CONTINUE
          WRITE(4'I) (MAP(I,J),J=1,M)
70          CONTINUE
          CLOSE(UNIT=4)
          WRITE(*,64) C01,C10
64          FORMAT(' C01:',I5,'x', 'C10:',I5)
          STOP
          END

```

APPENDIX E

PROGRAMS FOR K-L TRANSFORMATION, AND ONE-CHANNEL SEGMENTATION

```

C *****
C *
C * PROGRAM KRLV
C *
C * PURPOSE To implement Karhunen-Loève transformation from a 2-D
C * color image which size is 128 by 128 pixels.
C *
C * REQUIRED IMSL ROUTINES
C *
C * EIGRS, EQRT2S, EHOBKS, EHOUSS, UERTST, USPKD, UGETIO
C *
C * IMPLEMENTED BY LTJG TIMUR KUPELI Dec 1986
C *****
C
C   INTEGER I,J,L,K,N1,N2,NN,ROW,COL,ITEMP,QC(128,128),
C *   MAXVAL,MINVAL,IDIF,INTVAL,N
C
C   REAL R(1:3,1:3),E(1:3,1:3),FINPUT(1:128,1:128,1:3),
C *   D(3),WK(3),TEMP,Q(1:128,1:128,1:3),SLOPE
C
C   CHARACTER*50 IMAGE(1:3) , FNAME(1:3)
C
C   BYTE BINPUT(1:128,1:128),QQ(1:128,1:128,1:3)
C
C   TYPE 100
100  FORMAT( 'ENTER THE NUMBER OF ROWS, COLUMNS IN THE IMAGE', $ )
C   READ 101,N
101  FORMAT(I3)
C
C   TYPE 102
102  FORMAT( ' ENTER THE NUMBER OF CHANNELS IN THE IMAGE', $ )
C   READ 101,K
C
C   GET THE FILENAMES OF THE RED, GREEN, AND BLUE COMPONENTS
C   OF THE COLOR IMAGE.
C
C   DO 1 I = 1 , K
C   WRITE(*,2) I
2   FORMAT( ' ENTER THE FILENAME OF THE IMAGE CHANNEL NUMBER ', I, ',12,$ )
C   READ(*,3) IMAGE(I)
C   WRITE(*,3) IMAGE(I)
C   WRITE(*,45)
3   FORMAT(A50)
C
C   CONVERT THE IMAGE BTYPE FORMAT TO THE REAL NUMBER FORMAT
C
C   OPEN(UNIT=1, FILE=IMAGE(I), STATUS='OLD', ACCESS='DIRECT')
C
C   DO 5 ROW = 1 , N
C   READ(1,ROW) (BINPUT(ROW,COL), COL=1,N)
C   DO 6 COL = 1 , N
C   TEMP = BINPUT(ROW,COL)
C   IF (TEMP.LT.0.0) THEN
C   TEMP = TEMP + 256
C   END IF
C   FINPUT(ROW,COL,I) = TEMP
6   CONTINUE
5   CONTINUE

```

```

C      CLOSE(UNIT = 1)
C
C 1    CONTINUE
C
C      CALCULATE THE CORRELATION MATRIX
C
      NN = N * N
      DO 20 I = 1, K
        DO 21 J = 1, K
          R(I,J) = 0
          DO 22 N1 = 1, N
            DO 23 N2 = 1, N
              R(I,J) = R(I,J) + FINPUT(N1,N2,I)*FINPUT(N1,N2,J)
            23 CONTINUE
          22 CONTINUE
          R(I,J) = R(I,J) / NN
        21 CONTINUE
      20 CONTINUE
C
      WRITE(*,45)
      WRITE(*,30)
      WRITE(*,39)
      39 FORMAT('-----')
      30 FORMAT(' ',5X,' THE CORRELATION MATRIX', $)
      WRITE(*,31) ((R(I,J),J=1,K),I=1,K)
      31 FORMAT(<K>(F9.2,4X))
      WRITE(*,39)
C
C      CALCULATE EIGENVALUES AND EIGENVECTORS OF THE
C      CORRELATION MATRIX
C
      JOBN = 11
C
      CALL EIGRS(R,K,JOBN,D,E,K,WK,IER)
C
C      SORT THE EIGENVALUES IN DECREASING ORDER
C
      TEMP = D(1)
      D(1) = D(3)
      D(3) = TEMP
C
      DO 49 I = 1, K
        TEMP = E(I,1)
        E(I,1) = E(I,3)
        E(I,3) = TEMP
      49 CONTINUE
C
      WRITE(*,39)
      WRITE(*,45)
      45 FORMAT(' ')
C
      WRITE(*,41)
      WRITE(*,39)
      41 FORMAT(' ',5X,' THE EIGENVALUES ', $)
      DO 46 J=1,K
        WRITE(*,42) D(J)
      42 FORMAT(5X,F9.2)
      46 CONTINUE
      WRITE(*,39)
      WRITE(*,45)
      WRITE(*,43)
      WRITE(*,39)
      43 FORMAT(' ',5X,' THE EIGENVECTORS', $)
      WRITE(*,44) ((E(I,J),J=1,K),I=1,K)
      44 FORMAT(3(F9.2,4X))
      WRITE(*,39)
C
C      USE THE TRANSPOSE OF THE EIGENVECTORS MATRIX TO IMPLEMENT

```

```

C      KARHUNEN-LOEVE TRANSFORMATION.
C
      DO 50 I = 1, K
        DO 51 N1 = 1, N
          DO 52 N2 = 1, N
            Q(N1,N2,I) = 0.0
            L = 4 - I
            DO 53 J = 1, K
              Q(N1,N2,I) = Q(N1,N2,I) + E(J,I)*FINPUT(N1,N2,J)
53          CONTINUE
52        CONTINUE
51      CONTINUE
50    CONTINUE
C
      DO 60 I = 1, K
        WRITE(*,61) I
61      FORMAT(' ENTER FILENAME OF THE TRANSFORMED IMAGE ', ' ', I2, $)
        READ(*,3) FNAME(I)
        WRITE(*,3) FNAME(I)
        WRITE(*,45)

C      CONVERT THE TRANSFORMED IMAGE TO BYTE FORMAT
C
      DO 62 N1 = 1, N
        DO 63 N2 = 1, N
          QC(N1,N2) = JNINT(Q(N1,N2,I))
63      CONTINUE
62    CONTINUE
C
C      SCALE THE TRANSFORMED IMAGE TO BE WITHIN DISPLAY RANGE
C
      IF (I.EQ. 1) THEN
        MAXVAL = QC(1,1)
        MINVAL = QC(1,1)
        DO ROW = 1, N
          DO COL = 1, N
            IF (QC(ROW,COL) .GT. MAXVAL) THEN
              MAXVAL = QC(ROW,COL)
            ELSE IF (QC(ROW,COL) .LT. MINVAL) THEN
              MINVAL = QC(ROW,COL)
            END IF
          ENDDO
        ENDDO
        INTVAL = MAXVAL - MINVAL
        SLOPE = 255 / REAL(INTVAL)
        DO ROW = 1, N
          DO COL = 1, N
            IF (QC(ROW,COL) .EQ. MINVAL) THEN
              QC(ROW,COL) = 0
            ELSE IF (QC(ROW,COL) .EQ. MAXVAL) THEN
              QC(ROW,COL) = 255
            ELSE
              IDIF = QC(ROW,COL) - MINVAL
              QC(ROW,COL) = INT(SLOPE*IDIF)
            END IF
          ENDDO
        ENDDO
      ELSE
        MINVAL = QC(1,1)
        DO ROW = 1, N
          DO COL = 1, N
            IF (QC(ROW,COL) .LT. MINVAL) THEN
              MINVAL = QC(ROW,COL)
            END IF
          ENDDO
        ENDDO
        DO ROW = 1, N
          DO COL = 1, N
            IDIF = QC(ROW,COL) - MINVAL

```

```

                                QC(ROW,COL) = INT(SLOPE*IDIF)
                                ENDDO
                                END IF
C
DO 64 N1 = 1 , N
DO 65 N2 = 1 , N
                                ITEMP = QC(N1,N2)
                                IF (ITEMP .GT.127) THEN
                                    ITEMP = ITEMP - 256
                                END IF
                                QQ(N1,N2,I) = ITEMP
65 CONTINUE
64 CONTINUE
C
* OPEN(UNIT=2,FILE=FNAME(I),STATUS='NEW',ACCESS='DIRECT',
    RECL= (N/4), MAXREC=N )
C
DO 66 N1 = 1 , N
WRITE(2,N1) (QQ(N1,N2,I),N2=1,N)
66 CONTINUE
C
CLOSE(UNIT= 2)
C
60 CONTINUE
C
STOP
END

```

```

*****
*
* PROGRAM FLTR2
*
* PURPOSE To develop two sets of filter parameters from a 2-D single
*          channel image which size is 128 by 128 pixels. These para-
*          meters are the mean, the covariance, and the filter
*          coefficients.
*
* REQUIRED IMSL ROUTINES
*
*          LEQT2F, LUDATN, LUELMN, LUREFN
*
* IMPLEMENTED BY LTJG TIMUR KUPELI Sep 1986
*****

      INTEGER*4      P,Q,ROW,COL,STARTN(2),STARTM(2),ENDN(2),ENDM(2),IDGT,
*                   PQ,RNROW,RNCOL,RRROW,CCOL,X,Y,
*                   HNNO,HMMO,HCOL,HROW,LNNO,LNMO,LCOL,LROW,RN,RM,IER

      REAL*4      SUM,TEMP,FINPUT(128,128),MEAN(2),WKAREA(28),
*               R(4,4),SI(4,1),IMATRX(1,1),B00,
*               KW(1,1),A(4,1),ISIZE

      CHARACTER*50  IMAGE,FILTER(2)

      BYTE         BINPUT(128)

      T = 2

      GET PROGRAM INPUT PARAMETERS.

      TYPE 10
10  FORMAT(' ENTER NUMBER OF FILTER ROWS FROM 2-4 DESIRED :',5)
      READ 11,P
11  FORMAT(I3)

      TYPE 12
12  FORMAT(' ENTER NUMBER OF FILTER COLUMNS FROM 2-4 DESIRED :',5)
      READ 11,Q

      TYPE 13
13  FORMAT(' ENTER NUMBER OF ROWS IN IMAGE ',5)
      READ 11,N

      TYPE 14
14  FORMAT(' ENTER NUMBER OF COLUMNS IN IMAGE ',5)
      READ 11,M

      GET FILENAME OF SINGLE CHANNEL IMAGE

      TYPE 15
15  FORMAT(' ENTER FILENAME OF IMAGE ',5)
      READ 16,IMAGE
16  FORMAT(A50)

      CONVERT THE IMAGE BYTE FORMAT TO REAL NUMBER FORMAT

      OPEN(UNIT=1,FILE=IMAGE,STATUS='OLD',ACCESS = 'DIRECT')
      DO 17 ROW = 1, N
        READ (1,'ROW') (BINPUT(COL),COL=1,M)
        DO 18 COL = 1, M
          TEMP = BINPUT(COL)
          IF (TEMP.LT.0.0) THEN
            TEMP = TEMP + 256
          END IF
          FINPUT(ROW,COL) = TEMP
        DO 18 COL = 1, M
      DO 17 ROW = 1, N

```



```

18          CONTINUE
17  CONTINUE
    CLOSE (UNIT=1)

C
C
C  GET 'T' AREAS FOR WHICH FILTERS ARE DESIRED AND OUTPUT FILENAME FOR
    EACH AREA'S FILTER COEFFICIENTS AND COVARIANCE MATRIX.

    DO 19 I = 1,T
      WRITE(*,20) I
20    FORMAT(' ENTER UPPER-LEFT ROW FOR AREA ',I2,':',',$',
      READ(*,11) STARTN(I)

C
      WRITE(*,21) I
21    FORMAT(' ENTER UPPER-LEFT COLUMN FOR AREA ',I2,':',',$',
      READ(*,11) STARTM(I)

C
      WRITE(*,22) I
22    FORMAT(' ENTER LOWER-RIGHT ROW FOR AREA ',I2,':',',$',
      READ(*,11) ENDN(I)

C
      WRITE(*,23) I
23    FORMAT(' ENTER LOWER-RIGHT COLUMN FOR AREA ',I2,':',',$',
      READ(*,11) ENDM(I)

C
      WRITE(*,24) I
24    FORMAT(' ENTER OUTPUT FILE-SPEC FOR FILTER ',I2,':',',$',
      READ(*,16) FILTER(I)

C
C
C  FIND THE MEAN VECTOR OF ESTIMATION WINDOW AREA OF IMAGE

    ISIZE = (ENDN(I) - STARTN(I) + 1)*(ENDM(I) - STARTM(I) + 1)
    SUM = 0.0
    DO 25 L = STARTN(I),ENDN(I)
      DO 26 J = STARTM(I),ENDM(I)
        SUM = SUM + FINPUT(L,J)
26      CONTINUE
25    CONTINUE
    MEAN(I) = SUM / ISIZE
    WRITE(*,27) I,MEAN(I)
27    FORMAT(' MEAN ',(' ',I2,')',',',',F9.2,$)

C
C
C  CORRECT THE IMAGE TO BE ZERO MEAN

    DO 28 L = STARTN(I),ENDN(I)
      DO 29 J = STARTM(I),ENDM(I)
        FINPUT(L,J) = FINPUT(L,J) - MEAN(I)
29      CONTINUE
28    CONTINUE

C
C
C  DETERMINE CORRELATION MATRIX

    WRITE(*,291) I
291  FORMAT(' CORRELATION.MATRIX ',I2,$)
    PQ = P * Q
    DO 30 RNROW = 1,P
      X = 0 * (RNROW-1)
      DO 31 RNCOL = 1,P
        NO = RNROW - RNCOL
        Y = 0 * (RNCOL-1)
        DO 32 RMROW = 1,Q
          RN = X + RMROW
          DO 33 RMCOL = 1,Q
            MO = RMROW - RMCOL
            RM = Y + RMCOL
            LNNO = STARTN(I) + NO
            LMNO = STARTM(I) + MO
            HNNO = ENDN(I) + NO
            HMNO = ENDM(I) + MO

```



```

C      WRITE(2,50) KW(1,1)
50     FORMAT(F10.5)
      WRITE(2,500) MEAN(I)
500    FORMAT(F10.5)
      DO 51 J = 1,PQ
      WRITE(2,52) A(J,1)
51     CONTINUE
52     FORMAT(F10.5)
C      CLOSE(UNIT=2)
C      WRITE(*,53) I
53     FORMAT('  FILTER COEFFICIENTS  ',I2,$)
      WRITE(*,54) (A(J,1),J=1,PQ)
54     FORMAT(F10.5)
19     CONTINUE
      STOP
      END

```

```

C *****
C *
C * PROGRAM SGMT2
C *
C * PURPOSE To segment a single image with two textures given the
C * image, the image dimensions, the filter dimensions,
C * and two sets of filter parameters to be used.
C *
C * REQUIRED IMSL ROUTINES
C *
C * NONE
C *
C * IMPLEMENTED BY LTJG TIMUR KUPELI Sep 1986
C *****
C
C * INTEGER IN,N,IM,P1,P,Q1,Q,TMAX,T,PQ,ROW,COL,I,J,JJ,JJJ,L,LL,
C * LLL,LLLL,COUNT,LI,HI,LJ,HJ
C
C * REAL KW(2),MEAN(2),AA(4,1,2),TEMP,SUM1,SUM2,TEXTUR(128,128,2),
C * LN(2),ERROR(128,128,2),PML1,PML2,PML(128,128),
C * AREA,KS,A(2,2)
C
C CHARACTER*50 IMAGE,FNAME,MLTEST,MAPTEST
C
C BYTE BINPUT(128,128),ML(128,128),MAP(128,128),MLI(128,128)
C
C IN = 128
C IM = 128
C P1 = 4
C Q1 = 4
C TMAX = 2
C
C GET THE INPUT PARAMETERS OF THE PROGRAM
C
C 1 WRITE(*,2) IN
C 2 FORMAT(' ENTER THE NUMBER OF ROWS IN IMAGE.LIMIT OF',I3,':', '$)
C 3 READ(*,3) N
C 3 FORMAT(I3)
C IF((N.LT.1) .OR. (N.GT.IN)) GOTO 1
C
C 4 WRITE(*,5) IM
C 5 FORMAT(' ENTER THE NUMBER OF COLUMNS IN IMAGE.LIMIT OF',I3,':', '$)
C 5 READ(*,3) M
C IF((M.LT.1) .OR. (M.GT.IM)) GOTO 4
C
C 6 WRITE(*,7) P1
C 7 FORMAT(' ENTER THE NUMBER OF ROWS IN FILTER.LIMIT OF',I3,':', '$)
C 7 READ(*,3) P
C IF((P.LT.2) .OR. (P.GT.P1)) GOTO 6
C
C 8 WRITE(*,9) Q1
C 9 FORMAT(' ENTER THE NUMBER OF COLUMNS IN FILTER.LIMIT OF',I3,':', '$)
C 9 READ(*,3) Q
C IF((Q.LT.2) .OR. (Q.GT.Q1)) GOTO 8
C
C 10 WRITE(*,11) TMAX
C 11 FORMAT(' ENTER NUMBER OF TEXTURES TO PROCESS.LIMIT OF',I3,':', '$)
C 11 READ(*,3) T
C IF((T.LT.2) .OR. (T.GT.TMAX)) GO TO 10
C
C GET THE SINGLE-CHANNEL IMAGE
C
C PQ = P * Q
C WRITE(*,20)
C 20 FORMAT(' ENTER FILENAME OF IMAGE ', '$)
C 21 READ(*,21) IMAGE
C 21 FORMAT(A50)

```

```

C      OPEN(UNIT=1,FILE=IMAGE,STATUS='OLD',ACCESS='DIRECT')
C
C      DO 22 ROW = 1, N
C          READ(1,ROW) (BINPUT(ROW,COL),COL = 1, M)
22      CONTINUE
C
C      CLOSE(UNIT = 1)
C
C      GET THE FILTER COEFFICIENTS, MEANS, AND COVARIANCES
C
C      DO 23 I = 1, T
C          WRITE(*,24) I
24      FORMAT(' ENTER THE FILENAME OF FILTER PARAMETERS SET NUMBER',I2,':',S)
C          READ(*,21) FNAME
C
C          OPEN(UNIT=2,FILE=FNAME,STATUS='OLD')
C
C          READ(2,240) KW(I)
240      FORMAT(F10.5)
C          READ(2,240) MEAN(I)
C          DO 242 KK = 1, P
C              READ(2,240) AA(KK,1,I)
C
C          242      CONTINUE
C
C          CLOSE(UNIT = 2)
C
C          WRITE(*,241) KW(I),MEAN(I),AA(1,1,I),AA(2,1,I),AA(3,1,I),AA(4,1,I)
241      FORMAT(6F10.5)
C          23      CONTINUE
C          READ(*,220) MLTEST
C          READ(*,220) MAPTEST
220      FORMAT(A80)
C
C      CONVERT A 2-D BYTE INPUT IMAGE DATA IN THE RANGE OF -128 TO 127 THAT
C      REPRESENTS APPROPRIATE INTENSITY LEVELS IN THE RANGE OF 0 TO 255
C
C      DO 30 ROW = 1, N
C          DO 31 COL = 1, M
C              TEMP = BINPUT(ROW,COL)
C              IF(TEMP.LT.0.0) TEMP = TEMP+256
C              TEXTUR(ROW,COL,1) = TEMP - MEAN(1)
C              TEXTUR(ROW,COL,2) = TEMP - MEAN(2)
C
C          31      CONTINUE
C          30      CONTINUE
C
C      CALCULATOIN OF ERROR ESTIMATE FOR TWO TEXTURES
C
C      DO 40 I = 1, T
C          J = 1
C          DO 41 JJ = 1, P
C              DO 42 JJJ = 1, Q
C                  A(JJ,JJJ) = AA(J,1,I)
C                  J = J + 1
C              42      CONTINUE
C          41      CONTINUE
C
C          DO 43 L = 1, N
C              DO 44 LL = 1, M
C                  ERROR(L,LL,I) = 0.0
C                  DO 45 LLL = 1, P
C                      J = L - LLL
C                      DO 46 LLLL = 1, Q
C                          JJ = LL - LLLL
C                          IF((J.GT.0).AND.(JJ.GT.0)) THEN
C                              ERROR(L,LL,I) = ERROR(L,LL,I) + A(LL,LLLL)*TEXTUR(J,JJ,I)
C                          END IF
C                      46      CONTINUE
C                  45      CONTINUE
C              44      CONTINUE
C          43      CONTINUE
C
C          40      CONTINUE

```

```

45      CONTINUE
44      CONTINUE
43      CONTINUE
C
      LN(I) = ALOG(KW(I))
40      CONTINUE
C
C      CALCULATION OF MAXIMUM LIKELIHOOD IMAGE SEGMENTATION
C
      * OPEN(UNIT=3,FILE=MLTEST,STATUS='NEW',ACCESS='DIRECT',
          RECL=(IM/4),MAXREC=IN)
C
      L = 1
      LL = 2
      DO 50 I = 1, N
          DO 51 J = 1, M
              PML1 = 0.0
              PML2 = 0.0
              PML1 = ((ERROR(I,J,L)**2)/KW(L)) + LN(L)
              PML2 = ((ERROR(I,J,LL)**2)/KW(LL)) + LN(LL)
              PML(I,J) = PML2 - PML1
              IF(PML1.GT.PML2) THEN
                  ML(I,J) = -1
              END IF
              MLI(I,J) = ML(I,J)
          51      CONTINUE
      50      WRITE(3'I) (ML(I,J),J=1,M)
      CONTINUE
C
      CLOSE(UNIT=3)
C
      MAXIMUM A POSTERIORI IMAGE SEGMENTATION
C
      * OPEN(UNIT=4,FILE=MAPTEST,STATUS='NEW',ACCESS='DIRECT',
          RECL=(IM/4), MAXREC = IN)
C
      KS = 100
      DO 600 II = 1, 5
          DO 60 I = 1, N
              DO 61 J = 1, M
                  SUM1 = 0.0
                  SUM2 = 0.0
                  LI = I - 3
                  HI = I + 3
                  LJ = J - 3
                  HJ = J + 3
C
                  IF(LI.EQ.0) LI = 1
                  IF(HI.GT.N) HI = N
                  IF(LJ.EQ.0) LJ = 1
                  IF(HJ.GT.M) HJ = M
C
                  AREA = (HI - LI + 1) * (HJ - LJ + 1)
C
                  DO 62 ROW = LI, HI
                      DO 63 COL = LJ, HJ
                          IF((ROW.NE.I).OR.(COL.NE.J)) THEN
                              SUM1 = SUM1 - MLI(ROW,COL)
                          END IF
                      63      CONTINUE
                  62      CONTINUE
                  MAP(I,J)=0
C
                  SUM2 = PML(I,J) - ((KS/AREA)*(2*SUM1-AREA+1))
                  IF(SUM2.LT.0) THEN
                      MAP(I,J) = -1
                  END IF
              61      CONTINUE
          60      CONTINUE
      600      CONTINUE

```

```

        MLI(I,J) = MAP(I,J)
61      CONTINUE
60      CONTINUE
600     CONTINUE
C
        DO 70 I = 1, N
        WRITE(4,'I) (MAP(I,J),J=1,M)
70      CONTINUE
        STOP
        END

```

LIST OF REFERENCES

1. Therrien, Charles W., "An Estimation - Theoretic Approach to Terrain Image Segmentation," *Computer Vision, Graphics, and Image Processing* 22, pp. 313-326, 1983.
2. Janecek, J.F., *Algorithm for Segmentation of Multichannel Images*. M.S.Thesis, Naval Postgraduate School, Monterey, California, December 1985.
3. Hunt, B.R., Kubler, O., "Karhunen-Loeve Multispectral Image Restoration, Part I: Theory," *IEEE Transaction on Acoustics, Speech, and Signal Processing*, Vol. Assp-32, No.3, pp. 592-600, June 1984.
4. Makhoul, John, "Linear Prediction : A Tutorial Review," *Proc.IEEE* 63 pp. 561-580, 1975.
5. NPS Report NPS-62-87-002 "The Analysis of Multichannel Two-Dimensional Random Signals," by Therrien, C.W., 31 October 1986.
6. Therrien, Charles W., Quatieri, T.F., Dudgeon, D.E., "Statistical Model-Based Algorithms for Image Analysis," *Proceedings of the IEEE*, Vol.74, pp. 532-551, 1986.
7. Pratt, W.K., *Digital Image Processing*, New York:Wiley, 1978.
8. Pratt, W.K., "Spatial Transform Coding of Color Images," *IEEE Trans. on Communication Technology*, Vol. Com-19, No.6, 1971.
9. Rosenfeld A, Kak A.C., *Digital Picture Processing* Vol.2, New York, 1982.

INITIAL DISTRIBUTION LIST

	No. Copies
1. Defense Technical Information Center Cameron Station Alexandria, Virginia 22304-6145	2
2. Library, Code 0142 Naval Postgraduate School Monterey, California 93943-5002	2
3. Deniz Kuvvetleri Komutanligi Bakanliklar, Ankara / Turkey	5
4. Deniz Harp Okulu Komutanligi Kutuphanesi Tuzla, Istanbul / Turkey	1
5. Department Chairman, Code 62 Electrical and Computer Engineering Dept. Naval Postgraduate School Monterey, California 93943-5000	1
6. Professor Charles W. Therrien, Code 62Ti Electrical and Computer Engineering Dept. Naval Postgraduate School Monterey, California 93943-5000	3
7. Professor Chin-Hwa Lee, Code 62Le Electrical and Computer Engineering Dept. Naval Postgraduate School Monterey, California 93943-5000	3
8. Ltjg. Timur Kupeli Bati Lojmanlari, Cerbe B-1, Yuzbasilar Golcuk, Kocaeli / Turkey	3

LMED
-8